

# **Periodic Vibrotactile Guidance**

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT  
OF THE REQUIREMENTS FOR THE DEGREE OF

**Doctor of Philosophy**

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL  
STUDIES

(Computer Science)

The University Of British Columbia

(Vancouver)

October 2014

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# Abstract

Emergence of mobile technologies, with their ever increasing computing power, embedded sensors, and connectivity to the Internet has created many new applications such as navigational guidance systems. Unfortunately, these devices can become problematic by inappropriate usage or overloading of the audiovisual channels. Wearable haptics has come to the rescue with the promise of offloading some of the communication from the audiovisual channels.

The main goal of our research is to develop a spatiotemporal guidance system based on the potentials and limitations of the sense of touch. Our proposed guidance method, Periodic Vibrotactile Guidance (PVG), guides movement frequency through periodic vibrations to help the user achieve a desired speed and/or finish a task in a desired time. We identify three requirements for a successful PVG system: accurate measurement of the user's movement frequency, successful delivery of vibrotactile cues, and the user's ability to follow the cues at different rates and during auditory multitasking.

In Phase 1, we study the sensitivity of different body locations to vibrotactile cues with/without visual workload and under different movement conditions and examine the effect of expectation of location and gender differences. We create a set of design guidelines for wearable haptics.

In Phase 2, we develop Robust Realtime Algorithm for Cadence Estimation (RRACE) which measures momentary step frequency/interval via frequency-domain analysis of accelerometer signals available in smartphones. Our results show that, with a 95% accuracy, RRACE is more accurate than the published state-of-the-art time-based algorithm.

In Phase 3, we use the guidelines from Phase 1 and the RRACE algorithm to

study PVG. First we examine walkers' susceptibility to PVG which shows most walkers can follow the cues with 95% accuracy. Then we examine the effect of auditory multitasking on users' performance and workload, which shows that PVG can successfully guide the walker's speed during multitasking.

Our research expands the reach of wearable haptics and guidance technologies by providing design guidelines, a robust cadence detection algorithm, and Periodic Vibrotactile Guidance – an intuitive method of communicating spatiotemporal information in a continuous manner – which can successfully guide movement speed with little to no learning required.

# Preface

All work reported in this dissertation was conducted under the supervision of Dr. Karon E. MacLean (Department of Computer Science), who is my co-author on all work presented here. I was the primary contributor to all aspects of this research, however, there are several collaborators without whom this work could not have happened. In this preface, I describe the level of involvement of my collaborators, the resulting publications, and the ethics approval for conducting experiments with human participants.

This research was done in three phases and each phase started with software and/or hardware development followed by two experiments.

## **Phase 1: Sensitivity to Vibrations in Mobile Contexts**

This phase started out as a course project under the supervision of Dr. Karon E. MacLean and in collaboration with graduate students Zoltan Foley-Fisher, Russel MacKenzie, Sebastian Koch, and Mohamed El-Zohairy; it consisted of two experiments. We all equally participated in conducting the first experiment. Zoltan Foley-Fisher helped with hardware development and the final statistical analysis; Russel MacKenzie helped with software development and initial statistical analysis; Sebastian Koch helped with software development; and I led the experimental design, conducted the statistical analysis, and documented the study. I was the sole conductor of the second experiment. I modified the hardware and software that we used in the previous experiment, made changes to the design of the experiment, conducted the study, and performed the statistical analysis. Both experiments were published and presented at The ACM CHI Conference on Human Factors in Computing Systems (CHI) in 2011:



- I. Karuei, K. E. MacLean, Z. Foley-Fisher, R. MacKenzie, S. Koch, and M. El-Zohairy. Detecting vibrations across the body in mobile contexts. In *Proceedings of the 2011 annual conference on Human factors in computing systems - CHI 11*, pages 3267-3276, 2011

This phase is explained in Chapter 3.

### **Phase 2: Cadence Detection**

The premise of the second phase was to develop a cadence detection algorithm, deploy it on an Android phone, test it and use it in the next phase. Initially, I supervised Bryan Stern, an undergraduate, who implemented the algorithm on Android. He then helped me with conducting a short indoor experiment on treadmill. I conducted the statistical analysis alone. I then supervised Michelle Chuang to further improve the software. Oliver Schneider, a masters student at the time who would later use our cadence estimation algorithm in his research, helped me in the planning of the main experiment. Oliver and Michelle both helped me conduct the experiment. Oliver also reimplemented the time-domain algorithm that we compared our algorithm against. I then analyzed the results of the experiment and compared our algorithm and the time-domain one. Oliver helped me with the writing of these results and we published it in the *Journal of Pervasive and Mobile Computing*:

- I. Karuei, O. S. Schneider, B. Stern, M. Chuang, and K. E. MacLean. RRACE: Robust Realtime Algorithm for Cadence Estimation. *Pervasive and Mobile Computing*, (0):52–66, 2014. ISSN 1574-1192

This phase is explained in Chapter 4.

In a work not covered in this dissertation, Oliver Schneider supervised Mike Wu, an undergraduate, to extend our algorithm into a library called *GaitLib*. I provided advisory input to this paper, and am therefore included as a co-author.

### **Phase 3: Study of Periodic Vibrotactile Guidance**

In the third and last phase of this research, I conducted two experiments where I used the RRACE algorithm we developed in the previous phase and the *Haptic Notifier*, developed by Diane Tam, a masters student in our lab. I developed my

own code for the *Haptic Notifier* and developed an Android application that used the *GaitLib* to be used in the experiments. I conducted the first experiment.

In the second stage of this work, I supervised James Bigland, a cognitive science undergraduate, who helped me with the design of auditory tasks and conducting of the experiment. Finally, I analyzed the results of both experiments. The first experiment was published and presented at *Haptics Symposium* in 2014.

- I. Karuei and K. E. MacLean. Susceptibility to periodic vibrotactile guidance of human cadence. In *Haptics Symposium (HAPTICS), 2014 IEEE*, pages 141–146, 2014

This phase is explained in Chapters 5 and 6.

### **Research with Human Participants and Ethics**

All research with human participants was reviewed and approved by the University of British Columbia (UBC) Research Ethics Board under the B03-0490 and B01-0470 ethics approval. The amendment numbers and project titles for the associated certificates of approval are listed below:

***B03-0490:*** Sensitivity to Vibrations in Mobile Contexts, Part 1 (Chapter 3)

#### ***B01-0470***

- H01-80470-021: Sensitivity to Vibrations in Mobile Contexts, Part 2 (Chapter 3)
- H01-80470-024: Cadence Detection, Part 1 (Chapter 4) and Study of Periodic Vibrotactile Guidance Part 1 (Chapter 5)
- H01-80470-027: Cadence Detection, Part 2 (Chapter 4)
- H01-80470-034: Study of Periodic Vibrotactile Guidance, Part 2 (Chapter 6)

# Table of Contents

<b>Abstract</b> . . . . .	<b>ii</b>
<b>Preface</b> . . . . .	<b>iv</b>
<b>Table of Contents</b> . . . . .	<b>vii</b>
<b>List of Tables</b> . . . . .	<b>xiv</b>
<b>List of Figures</b> . . . . .	<b>xvi</b>
<b>Glossary</b> . . . . .	<b>xix</b>
<b>Acknowledgments</b> . . . . .	<b>xxii</b>
<b>Dedication</b> . . . . .	<b>xxiii</b>
<b>1 Introduction</b> . . . . .	<b>1</b>
1.1 Motivation . . . . .	2
1.2 Approach . . . . .	6
1.2.1 Requirements of PVG . . . . .	8
1.2.2 Applications of PVG . . . . .	10
1.2.3 Speculated Closed-loop Control of PVG . . . . .	13
1.3 Research Goals . . . . .	18
1.4 Research Approach . . . . .	18
1.4.1 Phase 1: Sensitivity to Vibrations in Mobile Contexts . . . . .	20
1.4.2 Phase 2: Cadence Detection . . . . .	20

1.4.3	Phase 3: Study of Periodic Vibrotactile Guidance . . . . .	21
1.5	Summary of Contributions . . . . .	22
1.6	Dissertation Roadmap . . . . .	23
<b>2</b>	<b>Related Work . . . . .</b>	<b>25</b>
2.1	Guidance Systems . . . . .	25
2.1.1	Non-haptic Guidance . . . . .	25
2.1.2	Stationary Haptic Guidance for Object Manipulation . . . . .	26
2.1.3	Haptic Guidance and Shared Control of Inland Vehicles . . . . .	27
2.1.4	Haptic Guidance for Training . . . . .	29
2.1.5	Haptic Situational Awareness Aid . . . . .	30
2.1.6	Wearable and Handheld Haptics and Spatial Guidance . . . . .	31
2.1.7	Non-haptic Temporal Guidance . . . . .	33
2.1.8	Haptic Feedback in Music . . . . .	34
2.1.9	Haptic Communication through Rhythm . . . . .	36
2.2	Spatial, Temporal, and Spatiotemporal Guidance . . . . .	37
2.2.1	Spatial Guidance . . . . .	37
2.2.2	Temporal Guidance . . . . .	37
2.2.3	Spatiotemporal Guidance . . . . .	38
2.3	Benefits and Drawbacks of Guidance . . . . .	39
2.3.1	Benefits of Guidance . . . . .	39
2.3.2	Drawbacks of Guidance . . . . .	41
2.4	The Haptic Channel . . . . .	43
2.4.1	Advantages of Haptic Channel . . . . .	43
2.4.2	Disadvantages and Limitations of Haptic Channel . . . . .	44
2.5	Tactile Display . . . . .	45
2.5.1	Technology . . . . .	46
2.5.2	Degrees of Freedom . . . . .	47
2.6	Summary . . . . .	49
<b>3</b>	<b>Detecting Vibrations Across the Body in Mobile Contexts . . . . .</b>	<b>50</b>
3.1	Introduction . . . . .	51
3.1.1	Approach . . . . .	52

3.2	Related Work . . . . .	53
3.2.1	Sensitivity to Vibrotactile Stimuli . . . . .	53
3.2.2	Wearable Haptic Systems . . . . .	54
3.3	Apparatus and Setup . . . . .	55
3.3.1	Vibrotactile Array and Calibration . . . . .	55
3.3.2	Movement Setup and Task . . . . .	57
3.3.3	Visual Workload Setup and Task . . . . .	57
3.3.4	Metrics and Analysis Technique . . . . .	58
3.4	Experiment 1: Random Site With Visual Load . . . . .	58
3.4.1	Design . . . . .	59
3.4.2	Procedure . . . . .	59
3.4.3	Results . . . . .	61
3.5	Experiment 2: Random vs Expected Site . . . . .	69
3.5.1	Design . . . . .	69
3.5.2	Results . . . . .	70
3.6	Summary and Discussion . . . . .	73
3.7	Conclusion and Future Work . . . . .	77
3.7.1	Design Guidelines . . . . .	78
3.7.2	Future Work . . . . .	80
3.8	Acknowledgment . . . . .	80
<b>4</b>	<b>Cadence Measurement . . . . .</b>	<b>81</b>
4.1	Introduction . . . . .	82
4.2	Related Work . . . . .	84
4.2.1	What is Realtime Cadence Detection Good For? . . . . .	84
4.2.2	Sensor Type . . . . .	86
4.2.3	Estimating Cadence . . . . .	87
4.2.4	Performance Assessment of Cadence Estimation Algorithms . . . . .	89
4.3	Approach: The RRACE Algorithm . . . . .	90
4.3.1	Overview . . . . .	90
4.3.2	Implementation Details . . . . .	91
4.3.3	Pseudocode . . . . .	92
4.3.4	Android-Based Validation Platform . . . . .	92

4.4	Experimental Validation of RRACE . . . . .	92
4.4.1	Treadmill-based Pilot Validation . . . . .	93
4.4.2	Primary Outdoor Walking Task and Measurement Apparatus	94
4.4.3	Experiment Design, Metrics, and Subjects . . . . .	97
4.4.4	Results for Outdoor Validation of 4 Second Window RRACE	98
4.4.5	Analysis of The Effect of Window Size on RRACE . . . . .	100
4.4.6	Power Consumption . . . . .	101
4.5	Comparing RRACE with a Threshold-based Time-domain Algorithm	103
4.5.1	Implementation of Time-based Algorithm for Comparison	103
4.5.2	Tuning of the Time-based Algorithm . . . . .	105
4.6	Discussion . . . . .	108
4.6.1	The Nature of RRACE's Error . . . . .	109
4.6.2	RRACE Meets Criteria for 4/6 of Tested Locations; Time- Based for 0/6 . . . . .	109
4.6.3	RRACE is Robust to Subject Differences . . . . .	110
4.6.4	RRACE is Sensitive to Very Slow Speeds . . . . .	110
4.6.5	RRACE Window Length of 4 Seconds is Best . . . . .	110
4.7	Conclusion and Future Work . . . . .	111
4.8	Acknowledgment . . . . .	112
<b>5</b>	<b>Susceptibility to Periodic Vibrotactile Guidance of Human Cadence</b>	<b>113</b>
5.1	Introduction . . . . .	114
5.2	Approach . . . . .	115
5.2.1	Contributions . . . . .	116
5.3	Related Work . . . . .	116
5.3.1	Perceptual Overload and Safety . . . . .	116
5.3.2	Spatial Vibrotactile Guidance . . . . .	117
5.3.3	Periodic Guidance of Locomotion . . . . .	118
5.3.4	Controlling Step Rate . . . . .	119
5.4	Experiment . . . . .	120
5.4.1	Apparatus and Context . . . . .	120
5.4.2	Experiment Design . . . . .	122
5.4.3	Computing Experimental Guidance Rates . . . . .	123

5.4.4	Procedures . . . . .	123
5.4.5	Metrics . . . . .	123
5.4.6	Analysis Technique . . . . .	124
5.4.7	Results . . . . .	125
5.4.8	Discussion . . . . .	128
5.5	Conclusions and Future Work . . . . .	129
5.5.1	Future Work . . . . .	131
5.6	Acknowledgment . . . . .	131
<b>6</b>	<b>Periodic Vibrotactile Guidance of Human Cadence, Performance during Auditory Multitasking . . . . .</b>	<b>132</b>
6.1	Introduction . . . . .	133
6.2	Approach . . . . .	135
6.2.1	Contributions . . . . .	136
6.3	Related Work . . . . .	136
6.3.1	Vibrotactile Guidance . . . . .	136
6.3.2	Guidance of Human Locomotion . . . . .	138
6.3.3	Temporal Guidance and Auditory Task . . . . .	139
6.3.4	Performance and Workload . . . . .	139
6.3.5	Measuring Cadence . . . . .	140
6.4	Experiment . . . . .	141
6.4.1	Experiment Design . . . . .	141
6.4.2	Guidance Conditions . . . . .	142
6.4.3	Auditory Tasks . . . . .	142
6.4.4	Metrics . . . . .	144
6.4.5	Apparatus and Context . . . . .	145
6.4.6	Procedures . . . . .	148
6.4.7	Data Preparation . . . . .	149
6.4.8	Analysis Technique . . . . .	150
6.5	Results . . . . .	151
6.5.1	Presentation of Results . . . . .	152
6.5.2	Cadence Error % . . . . .	152
6.5.3	Cadence . . . . .	153

6.5.4	Speed, Stride length, and Speed Ratio . . . . .	155
6.5.5	Workload . . . . .	155
6.6	Discussion . . . . .	155
6.6.1	Guidance Cue . . . . .	155
6.6.2	Effect of Auditory Task on Performance . . . . .	157
6.6.3	The User's Response Time . . . . .	158
6.6.4	Effect of Guidance on Workload . . . . .	158
6.6.5	Effect of Auditory Task on Workload . . . . .	159
6.6.6	Interpreting Subjective Workload Measures . . . . .	159
6.7	Conclusion . . . . .	160
6.8	Future Work . . . . .	161
6.9	Acknowledgment . . . . .	162
<b>7</b>	<b>Conclusion . . . . .</b>	<b>163</b>
7.1	Primary Research Contributions . . . . .	164
7.1.1	Study of Sensitivity to Vibrations in Mobile Contexts . . . . .	164
7.1.2	Development and Evaluation of RRACE . . . . .	165
7.1.3	Study of Periodic Vibrotactile Guidance of Human Walking . . . . .	166
7.2	Secondary Research Contributions . . . . .	168
7.2.1	Experimental Design and Methodology . . . . .	168
7.2.2	Data . . . . .	169
7.3	Reflections on Research Approach . . . . .	171
7.3.1	Visual Workload . . . . .	171
7.3.2	Sensory Adaptation, Learning, and Fatigue . . . . .	172
7.3.3	Step Detection . . . . .	173
7.3.4	Speed Measurement . . . . .	175
7.3.5	Robust Realtime Algorithm for Cadence Estimation . . . . .	176
7.3.6	Choosing the Range for Cadence and Speed . . . . .	177
7.3.7	Workload Measurement . . . . .	179
7.4	Future Directions . . . . .	180
7.4.1	Susceptibility to Periodic Guidance in Other Movements . . . . .	180
7.4.2	Study of PVG in Medium and Long Term . . . . .	180
7.4.3	Effect of PVG on Attention . . . . .	181



7.4.4	Other Use Cases for RRACE . . . . .	182
7.4.5	PVG’s Performance in Closed-loop Control Settings . . . . .	182
7.5	Closing Remarks . . . . .	183
	<b>Bibliography . . . . .</b>	<b>184</b>
<b>A</b>	<b>Supporting Materials: Detecting Vibrations Across the Body in Mobile Contexts . . . . .</b>	<b>207</b>
A.1	Ethics Documents . . . . .	207
A.2	Questionnaires . . . . .	214
<b>B</b>	<b>Supporting Materials: Cadence Measurement . . . . .</b>	<b>216</b>
B.1	Ethics Documents . . . . .	216
<b>C</b>	<b>Supporting Materials: Susceptibility to Periodic Vibrotactile Guidance of Human Cadence . . . . .</b>	<b>221</b>
C.1	Ethics Documents . . . . .	221
<b>D</b>	<b>Supporting Materials: Periodic Vibrotactile Guidance of Human Cadence, Performance during Auditory Multitasking . . . . .</b>	<b>226</b>
D.1	Ethics Documents . . . . .	226
D.2	Experiment Setup . . . . .	231
D.3	NASA Task Load Index (NASA-TLX) Screenshots . . . . .	231
D.4	Descriptive Statistics . . . . .	237

# List of Tables

Table 3.1	Body sites used in Experiments 1 and 2 . . . . .	61
Table 3.2	Generalized Linear Mixed Model (GLMM) of Detection Rate (DR) in Experiment 1 . . . . .	67
Table 3.3	Results of Kruskal-Wallis tests on Reaction Time (RT), Experiment 1 . . . . .	68
Table 3.4	GLMM of DR in Experiment 2 . . . . .	74
Table 3.5	Results of Kruskal-Wallis tests on RT, Experiment 2 . . . . .	75
Table 4.1	Walking Speeds During the Experiment . . . . .	95
Table 4.2	Experiment design . . . . .	97
Table 4.3	Error Ratio (ER) differences by Location on Person (LOP) for <i>four-second window</i> RRACE through an unpaired Z-test . . . . .	99
Table 4.4	RRACE ER differences by speed condition for 4 LOPs with a <i>four second window</i> (unpaired Z-test) . . . . .	100
Table 4.5	ER differences by window sizes of RRACE, with walking speed and LOP lumped . . . . .	101
Table 4.6	RRACE ER differences by LOP for all window sizes and walking speeds (unpaired Z-test) . . . . .	102
Table 4.7	Power consumption . . . . .	102
Table 4.8	Unpaired Z-test comparison of error ratios of the best and the worst versions of the frequency-based algorithm and the best of each category of time-based algorithm . . . . .	109

Table 5.1	Summary statistics of cadence error % by guidance condition for cue-on and cue-off . . . . .	125
Table 6.1	Auditory task conditions used in evaluation . . . . .	143
Table 6.2	Elements of Android wrist display . . . . .	146
Table 6.3	Vibrations used in study . . . . .	147
Table 6.4	Pairwise comparisons of <i>cadence error %</i> of auditory task levels per each guidance condition . . . . .	153
Table 6.5	Pairwise comparisons of cadence of auditory task levels per each guidance condition . . . . .	153
Table 7.1	Method of choosing speed or cadence rates in our experiments	179
Table D.1	Tempos used for techno music conditions . . . . .	231
Table D.2	Descriptive statistics of all metrics . . . . .	237
Table D.3	Descriptive statistics of performance metrics by guidance condition . . . . .	238
Table D.4	Descriptive statistics of performance metrics by auditory task .	239
Table D.5	Descriptive statistics of workload scores by guidance condition	240
Table D.6	Descriptive statistics of workload scores by auditory task . . .	241
Table D.7	Mean <i>cadence error %</i> per each level of auditory task guidance condition . . . . .	242
Table D.8	Mean <i>cadence</i> (Hz) per each guidance and auditory task condition	242
Table D.9	Statistical significance of all performance metrics . . . . .	242
Table D.10	Guidance condition's significant effect on cadence and pairwise comparisons of guidance conditions per each level of auditory task . . . . .	242
Table D.11	Statistical significance of all NASA-TLX scores and total workload	243

# List of Figures

Figure 1.1	Main parts of Periodic Vibrotactile Guidance . . . . .	9
Figure 1.2	PVG in a control setting . . . . .	14
Figure 1.3	A user’s location and speed response to the PVG system in three control settings . . . . .	17
Figure 1.4	The three phases of our research . . . . .	19
Figure 3.1	Setup of Experiment 1 during “walking with visual workload” condition . . . . .	56
Figure 3.2	VPM2 eccentric-mass factor . . . . .	57
Figure 3.3	Body sites used in Experiments 1 and 2 . . . . .	60
Figure 3.4	Mean Detection Rate and Reaction Time per body location in Experiment 1 . . . . .	62
Figure 3.5	Mean Detection Rate and Reaction Time for different intensities in Experiment 1 . . . . .	63
Figure 3.6	Mean Detection Rate per body location and condition in Experiment 1 . . . . .	64
Figure 3.7	Mean Reaction Time of high intensity stimuli per body location and condition in Experiment 1 . . . . .	65
Figure 3.8	DR per body location on the body map . . . . .	66
Figure 3.9	Mean Detection Rate and Reaction Time per body location in Experiment 2 . . . . .	71
Figure 3.10	Mean Detection Rate per body location and condition in Experiment 2 . . . . .	71

Figure 3.11	Mean Reaction Time of high intensity stimuli per body location and condition in Experiment 2 . . . . .	72
Figure 4.1	RRACE Pseudocode . . . . .	92
Figure 4.2	Experiment walkway, start and end points . . . . .	96
Figure 4.3	ER (ER) as a function of Speed Condition for 4-Second Window RRACE . . . . .	99
Figure 4.4	ER is a function of Window Size per each LOP for all Speed Conditions lumped . . . . .	101
Figure 4.5	ER is a function of Window Size per each Speed Condition for all LOPs lumped . . . . .	101
Figure 4.6	Example of the MPTrain time-based step detection algorithm .	104
Figure 4.7	ER compared for all algorithm variants and ordered by median	107
Figure 5.1	PVG regulates a walker's step frequency with subtle cues . . .	115
Figure 5.2	The <i>Haptic Notifier</i> and the <i>Xbee</i> USB radio . . . . .	121
Figure 5.3	Cadence by guidance rate when cue is on and off . . . . .	126
Figure 5.4	Cadence ratio by guidance rate, when cue is on and off . . . .	127
Figure 5.5	Cadence error % by guidance rate, when cue is on and off . .	128
Figure 5.6	Scatter plot of P4's <i>cadence</i> during trials 6-10 by guidance rate	129
Figure 5.7	Scatter plot of P4's <i>cadence error %</i> during trials 6-10 by guidance rate . . . . .	129
Figure 6.1	Experiment setup . . . . .	134
Figure 6.2	Data flow, throughout the experiment and during data processing	145
Figure 6.3	The <i>Haptic Notifier</i> and the <i>Xbee</i> USB radio . . . . .	146
Figure 6.4	Flowchart of the experiment . . . . .	149
Figure 6.5	All statistical effects visualized . . . . .	151
Figure 6.6	<i>Cadence error %</i> per guidance condition and auditory task . .	154
Figure 6.7	<i>Cadence</i> per guidance condition and auditory task . . . . .	154
Figure 6.8	<i>Speed, speed ratio, and stride length</i> per <i>guidance condition</i> and <i>auditory task</i> . . . . .	156
Figure 6.9	NASA-TLX results colour-coded by guidance condition and auditory task . . . . .	157

Figure D.1	NASA-TLX Screenshots - Part 1 . . . . .	232
Figure D.2	NASA-TLX Screenshots - Part 2 - 1/4 . . . . .	233
Figure D.3	NASA-TLX Screenshots - Part 2 - 2/4 . . . . .	234
Figure D.4	NASA-TLX Screenshots - Part 2 - 3/4 . . . . .	235
Figure D.5	NASA-TLX Screenshots - Part 2 - 4/4 . . . . .	236
Figure D.6	NASA-TLX Screenshots - Results . . . . .	236

# Glossary

<b>ANOVA</b>	Analysis of Variance, a set of statistical techniques to identify sources of variability between groups
<b>CHI</b>	The ACM CHI Conference on Human Factors in Computing Systems
<b>GPS</b>	Global Positioning System
<b>DGPS</b>	Differential Global Positioning System, an enhancement to Global Positioning System (GPS)
<b>PGS</b>	Personal Guidance System
<b>PFG</b>	Potential Field Guidance
<b>LAG</b>	Look-ahead Guidance
<b>DOF</b>	Degree of Freedom
<b>MIDI</b>	Musical Instrument Digital Interface
<b>MDS</b>	Multidimensional Scaling
<b>CPU</b>	Central Processing Unit
<b>PI</b>	Proportional-Integral
<b>PID</b>	Proportional-Integral-Derivative
<b>DTG</b>	Dynamic Tour Guide
<b>MRI</b>	Magnetic Resonance Imaging

<b>DR</b>	Detection Rate
<b>RT</b>	Reaction Time
<b>GLMM</b>	Generalized Linear Mixed Model
<b>SI</b>	The primary somatosensory cortex
<b>TTC</b>	Time to Collision
<b>PW</b>	Pulse-width
<b>RRACE</b>	Robust Realtime Algorithm for Cadence Estimation
<b>FASPER</b>	Fast Calculation of the Lomb-Scargle Periodogram
<b>ER</b>	Error Ratio
<b>FFT</b>	Fast Fourier Transform
<b>LOP</b>	Location on Person
<b>EWMA</b>	Exponentially-Weighted Moving Average
<b>FSR</b>	Force Sensing Resistor
<b>IMU</b>	Inertial Measuring Unit
<b>JNI</b>	Java Native Interface
<b>SPM</b>	Steps per Minute
<b>SPS</b>	Steps per Second
<b>PVG</b>	Periodic Vibrotactile Guidance
<b>PVC</b>	Periodic Vibrotactile Cue
<b>VT</b>	Vibrotactile
<b>LOESS</b>	Locally Weighted Regression, a way of estimating a regression surface through a multivariate smoothing procedure



- NASA-TLX** NASA Task Load Index, an instrument for gauging the subjective mental workload experienced by a human in performing a task
- SWAT** Subjective Workload Assessment Technique
- CLC** Closed-loop Control
- GLM** Generalized Linear Model
- HANS** Haptic Notification System
- MRT** Multiple Resource Theory

# Acknowledgments

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Karon MacLean, who supported and guided me from the moment I applied to the Ph.D. program through the end of this work. Whenever I felt discouraged by the results or an unsolvable dilemma, her advice helped me think out of the box to find a solution and her encouragement motivated me to work harder.

Besides my supervisor, I would like to thank the members of my supervisory committee: Drs. Todd Handy, Tania Lam, and Michiel van de Panne for their invaluable feedback throughout this work. I am also grateful to my examining committee members: Drs. Nadine Sarter, Machiel Van der Loos, and Darren Warburton for their very interesting questions and suggestions which further improved this dissertation.

I would like to give special thanks to Steve Yohanan, who always gave me great advice like a big brother, and Oliver Schneider, a wonderful collaborator and a great person to talk to about anything Computer Science related or otherwise. I must also thank my other collaborators: James Bigland, Bryan Stern, Mike Wu, Michelle Chuang, Zoltan Foley-Fisher, Russel MacKenzie, Sebastian Koch, and Mohamed El-Zohairy, without whom this research would not have happened. I am also thankful to my colleagues in the Sensory Perception and Interaction Research Group (SPIN) for their technical and moral support.

Furthermore, I thank my parents, Hamid Karuei and Haydeh Pishdad, my teachers ever since I started exploring the world who always praised curiosity and skepticism. Finally, words are powerless to express my gratitude to my wife, Mahtab Ghavami, who encouraged me at every step and supported me in many different ways during this journey.

# Dedication

To my parents, Haydeh and Hamid,  
and to my wife, Mahtab.

# Chapter 1

## Introduction

*If you want to find the secrets of the universe,  
think in terms of energy, frequency, and vibration.*

— Nikola Tesla

It is a sunny afternoon in a beautiful city, where you are attending a conference. You just had lunch with an old colleague, whom you had not seen for many years. You had planned to see him for an hour during the lunch break but your conversation got very interesting and continued longer than expected. Despite trying very hard not to be seen checking your watch you were caught and it felt uncomfortable. Eventually the conversation ended and now you are walking back to the conference hotel thinking that you have missed more than half of the first session in the afternoon. It is the second session that you should definitely attend because it is closely related to your field. You are nervous; you do not have much time, so you check your watch and take the conference schedule out of your pocket and look at it, that long list of talks and their lengths in awfully small fonts, while walking very fast; the lunch break was 80 minutes and you had not accounted for the coffee break between sessions. You actually have about 55 minutes until the next session. You feel relieved and calm, for about two seconds, until you hear a loud car horn and a man shouting at you in a language you do not understand; either because it is not your mother tongue or because it is too fast and unexpected. You jump to the sidewalk with fear and guilt. When you look up you see the conference hotel; you really did not think you could be there so fast. You enter the hotel and walk towards

the conference rooms. Now you take the conference schedule out of your pocket to check the room number; this time you stop walking. On your way to room B2, where you should be for part of the first session and all of the next one, you grab a glass of water, instead of black coffee which you usually drink. You open the door and feel that all eyes are on you, entering the room in the middle of a talk. There is no empty seat, so you must be standing up for the next 49 minutes. The slides seem very interesting and the speaker is great but you have no clue what the talk is about because you missed one third of it. Your eyes are on the screen but your mind is somewhere else. You are looking but not seeing, and hearing but not listening just like when you were walking a few minutes ago. You are wondering if you could have talked longer with your old colleague. You have already completely forgotten that you could have been run over by a car.

## 1.1 Motivation

The world we perceive has four dimensions, three spatial and one temporal. We are constrained by these dimensions but we try very hard to free ourselves from them. We created telescopes and maps to understand where we are on earth and in the universe, and we built ships to cross oceans, cars to travel on land, and airplanes to conquer the skies; but moving very fast was not sufficient, so we invented telephone, video conferencing, and teleoperated robots to perform tasks in far away locations, and to be, almost, in two or more places at the same time. With all those achievements, location has become less relevant in our lives and time has become the more important constraint. Albert Einstein once said that “*The only reason for time is so that everything doesn't happen at once*”. In a sense time is one more “degree of freedom” in our lives but we do not have much control over it. One strategy is trying to multitask; we talk over the phone while driving, send text messages while walking, and listen to radio shows while writing an essay; sometimes we are just lucky not to lose our lives or others' just for saving a few seconds. Another strategy we use is filling all spaces between tasks with other tasks; we have meetings at lunch breaks, send emails in between talks, and take the garbage out during TV commercials. This strategy is prone to failure too because it is very sensitive to uncertainties, although its direct consequences, being late for the next task for ex-

ample, may not be as terrible as the previous strategy. In reality, whenever possible we use both strategies at the same time. To reduce the likelihood of failure we plan ahead of time but it is not sufficient and there is not much more that we can do. In most cases, the events that jeopardize timing and performance of our tasks happen at micro level; when we fail to notice passage of time during a conversation, or when we see someone by chance on our way to the conference for example. Most of these “micro” events cannot be accounted for in a plan. Nevertheless, planning at micro level can be very time and energy consuming.

### **Powerful Computers in our Pockets**

Technology has come to our help, to “save time” whenever possible. We use Global Positioning System (GPS) devices that constantly receive traffic updates, smartphones (or smart watches nowadays) that update their time zone based on location, and application software such as to-do lists, calendars, and alarms that are improved everyday to accommodate us better and save us more time and energy. Most of these devices do magical things that ordinary users take for granted or fail to notice: they make, mostly, correct assumptions about location of the user and time of day and only inform him/her of relevant events; they take different daylight saving times of the countries that use them, and update them whenever countries decide to start or stop to use them. However, often times, these technological advances fail to help us perform better or even put us at more risk. Pedestrians use their smartphones while walking and even when crossing streets, not just to talk to somebody, but to read and send text messages, or use very engaging applications on their phones with their heads down and their ears not hearing the sound of approaching cars, which are getting faster and quieter by the way. Drivers do the same thing with one hand on the steering wheel and a foot on the gas pedal. One way to mitigate the negative effects is reducing usage, by passing laws for example, which is like erasing a question instead of answering it. Another way to reduce the negative effects, and possibly increase positive effects, is to make changes to the technology to address the user’s needs and constraints.

The tools that assist people with their daily planning provide them with temporal and/or spatial information (*e.g.*, watches, calendars, maps) or guide them through their tasks (*e.g.*, GPS). However, these tools fall short of ideal assistance

for the following reasons:

1. They occupy visual and auditory senses that should be dedicated to the primary task (*e.g.*, watching ahead while walking) or a parallel secondary task (*e.g.*, talking to another person).
2. They use vision and audition in situations where vision and audition are impaired (*e.g.*, fire fighters' vision impaired by smoke) or are not preferred (*e.g.*, alarm clock in a library).
3. They do not take the context and environment of the user into account (*e.g.*, a driver who may not hear GPS directions because of loud music or too much noise in the car).
4. They provide us with numerical values (*e.g.*, meeting in 30 minutes, 23 kilometers to destination) or abstract messages, some of which could be completely arbitrary from the user's point of view (*e.g.*, a beep sound representing a calendar alarm) which require cognitive processing.

### **Partial Fixes for The Issue**

To address the first and second issues, many have proposed substituting vision and audition with tactile and haptic perception [15, 37, 70, 158]. Tactile messages (or Haptic Icons) [14, 155] and haptic/tactile guidance for pedestrians [11, 35] are examples of substituting (or augmenting) audiovisual channels with the haptic channel. However, the most globally adopted example of this is the vibration alerts on mobile phones that replace auditory ringtones for two reasons: to be felt in noisy (*e.g.*, a concert) and quiet (*e.g.*, a library) environments. Due to their success in improving mobile phone interfaces, vibration alerts are the most widely used vibrotactile interactions, however, as will be discussed in Chapter 3, these vibrotactile cues do not take into account the fact that the user might be in motion and less sensitive to vibrations, especially on his/her thighs (*i.e.*, the user's pocket) where the device usually is.

Many interfaces present information as numerical values or abstract messages since it is the most straightforward solution in most situations (*e.g.*, a car's speedometer) but does not translate very well to the user's perception of time and space; for

example, most GPS devices notify the driver of the distance to a “highway exit” or a “left/right turn” in metric or imperial units and the driver should try to estimate the distance and make a judgment on where to turn or change lanes while the car is moving very fast. In contrast, humans use a much easier to understand language when they guide each other in space: “turn right after the gas station” or “see the red car on the right lane? follow that”. The same issue exists with presentation of temporal information but may not be quite as evident; the fact that we round up periods of time to hours and half hours while in reality we care about smaller fractions such as five minute periods (*e.g.*, we take 10 minute breaks, or allow 5 minute question periods) shows that we care about minutes but usually count hours to make life simpler. It may be harmless to take a one hour exercise instead of 62 minutes, but you may miss a bus if you try to be at the bus stop at 11:25 when the bus actually arrives at 11:23.

### **What is Really Needed**

We believe guidance systems (and any other interface for that matter) can be very efficient and intuitive if we (a) use the right medium, (b) avoid unnecessary abstractions, and (c) use the right mapping for information presentation.

*Using the right medium:* The right medium is the one that is not blocked, prohibited, or overly occupied in the context it is employed; we should note that this applies to all types of interfaces. Imagining a fire fighter looking at the graphical display of a handheld device in thick smoke is as absurd as a construction worker on a jackhammer wearing a vibrotactile belt.

*Avoiding unnecessary abstractions:* It is well understood that sometimes abstractions (*e.g.*, converting time to numbers, using different alarms for different purposes) are inevitable. However, there are times that we abstract information out of habit or tradition. For example, when a presenter looks at the timer on the podium, all he wants to know is if he is on time and should continue his talk in the same way or if he is behind schedule and should do something about it. If instead of seeing a four digit number – which could distract him for a moment, several times during the talk – he sees a smiley face on the timer, he can just continue his presentation and will only worry when the face changes.



***Using the right mapping for information presentation:*** When we present information, we map it from its actual form and we use units, numbers, or even colour and sound to communicate it to the user. This mapping can always be done in infinitely many ways, but most of them are hard to understand for the user. Understanding the user’s abilities and needs can help us make the presentation of information more beneficial to the user. In the above example, a smiley face is a good indicator but it ignores an important aspect of time: continuity. The presenter may know that he is on track or not, but he cannot know to what extent. If the smiley face would move to right (when the presenter was ahead) or left (when the presenter was behind), the presenter could easily understand the extent to which he is early or late and if his current pace is compensating for that.

In the next section, we present our idea for a new solution called Periodic Vibrotactile Guidance.

## **1.2 Approach**

***Periodicity:*** Our solution for the above problems comes from a simple idea: instead of providing users with abstract high-level information (*e.g.*, remaining time) which requires cognitive work to be translated to task related parameters (*e.g.*, how fast some aspect of a task should be done), we can provide them with lower-level parameters that are directly related to accomplishing a task. For example, when a person wants to catch a bus, he/she needs to check the bus schedule, subtract the bus arrival time with current time to know how much time he/she has, then decide when to walk towards the bus station. There are applications, mobile or otherwise, that go one step further and tell the user, based on average walking speed of people, approximately when the user should start to walk (*e.g.*, Google maps [55]). These applications partially solve the problem by doing the math for the user, but they are still bound in abstractions. What if we could communicate this information to the user in a way that the he/she would know, based on his/her own typical speed, when to start walking? We believe instead of communicating when, we can communicate “how fast” the user should be walking at any point in time and the user gets to choose. Obviously, the earlier the user starts to walk, the slower he/she needs to walk. This idea seems promising until you realize that there is no consistent and

accurate language for communicating absolute speed and this new solution very much relies on accuracy and consistency of communicating speed, otherwise users will not know what is the right speed and when is the right time. However, walking speed is tied to something else that is more closely related to our bipedal motion control: *cadence* (or stride frequency). Walking speed is the product of *cadence* and *stride length* as shown in Equation 1.1 where  $v$  is walking speed,  $f$  is stride frequency (cadence), and  $l$  is the stride length.

$$v = f \times l \tag{1.1}$$

These parameters are automatically adjusted based on energy efficiency in unconstrained normal walking [144]; however, each one of them can be constrained and it affects the other ones as well [67, 89]. As will be explained later in Section 6.3.2, stride length and frequency also vary as a function of speed.

Instead of trying to guide a user's speed, we can guide his/her cadence, by providing the desired cadence and requiring the user to synchronize his/her cadence with it; this is based on the assumption that if we constrain cadence, stride length will stay constant or change in the same direction as cadence. As will be discussed later in Chapter 6, by controlling the guidance cadence and adjusting it we can achieve high level goals such as the user's desired speed or desired time of arrival at a destination as shown in Equation 1.2 where  $t$  is the time until arrival,  $d$  is distance, and  $v$  is speed.

$$t = d/v \tag{1.2}$$

***Vibrotactile Cueing:*** At first glance an auditory cue with the desired tempo seems to be the perfect solution. Walking to the tempo of a metronome is very similar to dancing to the beat of music. In fact, it has already been shown that users can synchronize their *cadence* with the tempo of a metronome [29]. However, as explained in Section 1.1, the medium should fit the context. Auditory cues can easily be suppressed by the noise in the environment. Moreover, the auditory channel might be occupied for other activities such as participating in a conversation or listening

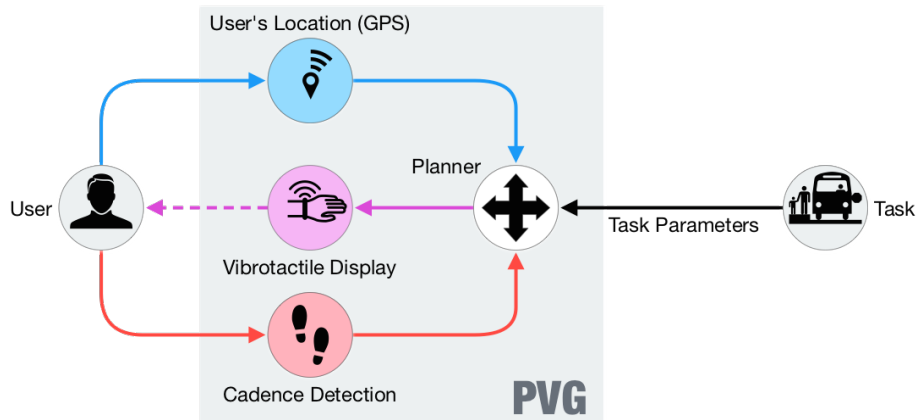
to a podcast or music during daily commutes and physical activities; this means that using auditory cues for guidance is almost impossible. In the face of these challenges, and considering that the vibrotactile cues offer the same solution for communicating tempo without the disadvantages of the auditory channel, we propose to use periodic vibrotactile signals to directly guide users by synchronization of cyclical movements. Furthermore, we emphasize the inclusion of temporal parameters in addition to spatial parameters for guidance. In this method, a wearable/handheld tactile display periodically vibrates, taps, or squeezes the user's skin to indicate pedaling, paddling, or stride frequency; it gives the user a new sensation of velocity or urgency by mapping spatiotemporal constraints into parameters of the haptic rhythm such as tempo. This sensation is similar to the sound of a car engine that indicates its revolutions per minute or the beat of music that helps a dancer synchronize with it. Because this method of speed control uses a very simple vibrotactile cue, it is fairly easy to learn and does not rely on memory which we believe causes very little workload.

### **1.2.1 Requirements of Periodic Vibrotactile Guidance (PVG)**

A Periodic Vibrotactile Guidance system has four main parts: speed and location measurement unit (*i.e.*, GPS), cadence detection unit, vibrotactile display, and the planner. These can be seen in Figure 1.1. Throughout this thesis, we assume that a user will be wearing a standard smartphone on his/her body (with few or minimal restrictions on how it is worn), with basic accelerometer and GPS functionality at a quality that was commonly available in 2012. In some examples, continuous location (GPS) data are important to an algorithmic variation, and in other cases not. The power-draw implications of this continuous sensing and computation in a wearable device were significant at the time of this writing, but expected to improve substantially in the near future due to advances in computational efficiency and more fine-grained control over processor function.

***Speed and Location Measurement:*** At every point in time the user's location and speed is measured by a GPS and sent to the planner.

***Cadence Detection:*** The user's cadence (stride frequency) is also measured in realtime and sent to the planner. In Chapter 4 we will present Robust Realtime



**Figure 1.1:** PVG consists of a GPS for speed and location estimation, vibrotactile display, cadence detection unit, and a planner; the planner receives the task parameters such as time and destination and the user's location, speed, and cadence and determines the tempo (and/or intensity) of the vibrotactile cues.

Algorithm for Cadence Estimation (RRACE), an algorithm that uses the input from accelerometers (that are available in most handheld devices) to measure the user's cadence.

**Planner:** The planner consists of:

- *Speed planner* which measures the user's desired speed based on time and destination.
- *Speed-cadence model* which is created (and updated as necessary) based on the user's cadence and speed measurements. This model can estimate the cadence associated with a desired speed.

**Vibrotactile Display:** consists of one or several eccentric-mass factors, placed in a wearable device in a way that vibrations from the tactors are easily felt on the skin; this means that the tactors should directly or through a sufficiently thin layer of material touch the skin. In Chapter 3 we study different options for placement of vibrotactile displays.

## 1.2.2 Applications of PVG

PVG has many temporal and spatiotemporal guidance applications in the daily lives of people. Temporal guidance systems are suitable for assisting users for tasks that are independent to location of users. Spatiotemporal guidance is a generalization of temporal guidance when the location of users also matters for the task.

### Temporal Guidance

PVG can help users manage their time, control their body movement frequency and speed, and synchronize themselves with a reference. The dominant element of the temporal guidance we are proposing here is its periodic, tightly resolved nature. We should note that using start/stop alerts for an entire event is also temporal guidance (*e.g.*, “start your run now”, “stop it now”, “the event is in 5 minutes and this is the only alert”) but it is not the focus of this dissertation. There are many potential applications for temporal guidance through PVG: handheld calendars, sport exercises, group synchronization, and performing arts. The following scenarios explain some temporal applications of PVG.

***Vibrotactile Timed Alerts:*** Instead of checking the calendar on the graphical display of a mobile phone, a user can keep it in his/her pocket until it starts vibrating slowly with a simple but identifiable rhythm. The user looks at the screen and remembers the event and puts the mobile phone back into his pocket. Based on the type and priority of the task, the mobile phone starts vibrating with the same rhythm and as it gets closer to the time of the event, the rhythm becomes faster and faster to give a feeling of time relative to the event. This also represents a natural feeling of urgency as the time of the event approaches.

***Wearable Guidance for Exercising:*** Athletes who prepare themselves for future events or just exercise to improve their abilities try to improve their speed, stamina, or strength gradually and over long periods of time. For them, it is very helpful to have a reference tempo for running, paddling, or cycling . It can be used to keep a constant tempo or to keep a record of past tempos for increasing it gradually during the training regimen (*e.g.*, days or weeks of training). The guidance system only needs to display the required tempo through vibrations. It can also measure

deviation from the desired frequency.

***Wearable/Mobile Guidance for Collaboration:*** In most live performances many agents collaborate with tight schedules. A coordinator informs everybody about the time of different actions or changes in schedule. PVG can be used in this scenario to make collaboration easier. The coordinator may update the time of the events and use a central device to communicate those timings to wearable PVG devices worn by his/her agents. As they approach the time of an event, the corresponding agent feels a significant increase in the heartbeat of wearable device and gets ready for the task he/she is responsible for.

***Vibrotactile Guidance in Synchronized Sports:*** Moving at the same frequency and with the same phase is the most important aspect of synchronized sports. The tempo and phase of movement can be communicated by a PVG device which does not rely on vision or audition and therefore allows athletes to use their vision for the primary task and does not get masked out by the noise. A team of rowers or paddlers can be synchronized by tappings of the guidance system on their shoulders or wrists. The frequency of tappings can be constant or be controlled by the leader of the team or their coach or an artificially intelligent system that optimizes the speed based on the information it collects about athletes by monitoring the signals from biosensors attached to their bodies.

***Vibrotactile Guidance in Performing Arts:*** Speed and rhythm of a performing artist is a very important factor which needs to be precise. The artist has to memorize the speed of performance and the ups and downs of it during the performance. Sometimes the rhythm of the music is a reference (if there is a rhythmic music) but even musicians need a reference for the speed and/or a reminder for different parts of the performance too (*e.g.*, conductor). A PVG system can help musicians and other performing artists by displaying a gentle and precise haptic rhythm which is hidden from the audience and does not get masked out by other sounds.

### **Spatiotemporal Guidance**

Spatiotemporal guidance can assist users with tasks that have temporal and spatial requirements. In other words, they can help users make the right decisions about

time and location of tasks. Pedestrians, drivers, workers, and athletes can benefit from spatiotemporal haptic guidance.

***Wearable Guidance for Pedestrians:*** A pedestrian needs to know when he/she should start walking and at what direction and speed, and for how long to reach his/her destination at a certain time. This destination can be a bus stop, a classroom, workplace, or a meeting. People usually depend on their own estimations which may cause them to be late or too early – *e.g.*, if the bus, whose current location your device might know, is delayed. PVG system can in fact, calculate the precise speed based on the time of arrival and convert it to *cadence* and communicate it to the user continuously until the user reaches his/her destination. Because the calculations can happen in realtime some unexpected events such as stopping to talk to someone or to get coffee can be considered as a disturbance and can automatically be taken care of as long as it is relatively short.

***Vibrotactile Spatiotemporal Navigation:*** A GPS device may visually or verbally communicate distance or time to turn to a pedestrian, cyclist, or driver, which requires the user to do estimations and depends on auditory and/or visual attention. However, replacing it with a haptic rhythm which gets faster as the user gets closer to a turning point gives the user a feeling of closeness to a point in time and/or space in a more natural way that does not need any verbal explanations.

***Vibrotactile Speed Control in Sports:*** An athlete needs to have a strategy for his movement speed. His speed may need to increase or decrease at different points. A spatiotemporal guidance system can assist in training of runners, cyclists, and rowers. Coaches can define a reference, fine-grained movement frequency (*e.g.*, gait or pedaling frequency), and use the guidance system to communicate it to the athlete during movement. PVG can also be used as a sensory augmentation method for athletes in competitive sports; it can notify athletes of the relative position or speed of the closest competitor, the distance behind or ahead of the winning pace, or the speed required for breaking a record.

### 1.2.3 Speculated Closed-loop Control of PVG

A PVG system works on a simple principle: it collects information about a task and the user and then creates appropriate Periodic Vibrotactile Cues to guide the user. This system can be built with up to two feedback loops. Although in this thesis we only implement open-loop control, it is useful to explore how a full implementation could play out. To understand this architecture better and particularly distinguish the two loops, we start with an open-loop system and build the closed-loop structure on top of that in two steps.

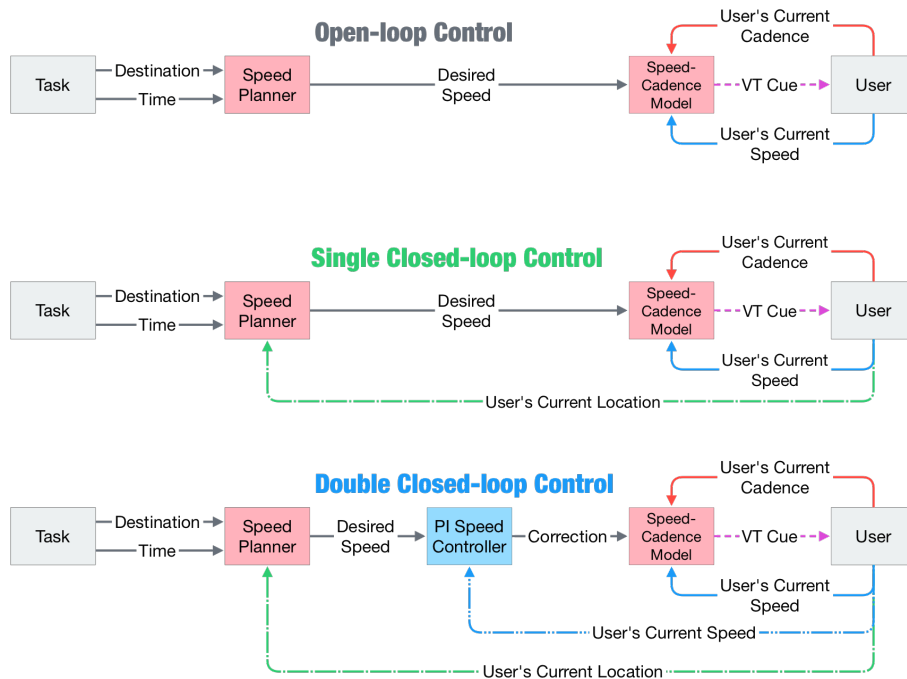
#### Open-loop Control

In the simplest form PVG can be a completely open-loop system as shown in Figure 1.2 (top). In this system, the guidance signal only relies on the input about the task and environment and is independent of the user's performance and state. In the case of *cadence* guidance, the system can compute desired speed of the user based on the distance to destination and desired time of arrival. The system also incorporates a *Cadence-Speed Model* based on past measurements or user history or an estimated average stride length, which can get updated as deemed necessary; the *Cadence-Speed Model* can then estimate the desired cadence and communicate it to the user through the tempo (and/or intensity) of the Periodic Vibrotactile Cues. If the user's performance is ideal (*e.g.*, the user walks exactly at the desired cadence) and the system's estimation of desired cadence is correct (*e.g.*, the cadence estimation of the desired speed for that particular user is correct) the user will be at his/her destination at the desired time. However, we can be sure that there is always some error in the estimation of the desired cadence. On the other hand, the user may not walk exactly at the displayed cadence. As a result, over time error accumulates and more likely than not grows in amplitude. In Figure 1.3, the red lines show the speed and location of a user who is given a constant *cadence* cue. Because the user walks slower than desired, he/she arrives late at the destination.

#### Single Closed-loop Control

The PVG system can easily reduce the estimation error and the user's divergence from the guidance cue by constantly updating the guidance cue based on the user's state (*i.e.*, time and location) as shown in Figure 1.2 (middle). If the user's speed is exactly as expected the guidance cue stays the same (even if there is substantial





**Figure 1.2:** PVG in a control setting. Open-loop control (top): PVG consists of a *Speed Planner* and *Speed-Cadence Model* which are shown as pink boxes; *cadence* and *speed* measurement (*i.e.*, measured by a GPS) units and the *vibrotactile display* are not explicitly presented as boxes but as red, blue, and purple (dashed-line) arrows from the user to the model. *Speed Planner* estimates the desired speed based on time and distance to destination and the *Speed-Cadence Model* – which is built based on the user’s speed and cadence (and updated as needed) – estimates the tempo of the vibrotactile cue (*i.e.*, desired cadence) according to the desired speed. Single closed-loop control (middle): speed estimation (desired speed) is updated constantly based on the user’s location, shown as green dash-dotted line arrow, (*e.g.*, measured by the GPS). Double closed-loop control (bottom): The input to the *Speed-Cadence Model* is adjusted based on the user’s current speed (*e.g.*, measured by the GPS) to minimize the difference between the user’s speed and the desired speed.

divergence between the cadence cue and the actual step rate). However, if the user's speed is slower (or faster) than desired, the speed setpoint<sup>1</sup> will adjust in response and the guidance cue will change accordingly to compensate for the lateness (or earliness) of the user.

One of the characteristics of this system is that if the user always walks slower (or always walks faster) than the setpoint, the setpoint constantly grows (contracts). To demonstrate this let us assume that  $T$  is the desired arrival time,  $X$  the destination location, and  $x(t)$  the user's location at time  $t$  (where  $t < T$ ). Controller's speed setpoint, and the user's speed can be defined by Equations 1.3 and 1.4 respectively, where  $V_c(t)$  is controller's speed setpoint, and  $V_u(t)$  is the user's speed.

$$V_c(t) = \frac{X - x(t)}{T - t} \quad (1.3)$$

$$V_u(t) = x'(t) \quad (1.4)$$

where “ $x'(t)$ ” (prime) indicates derivative with respect to time ( $t$ ). Using the *quotient rule*<sup>2</sup> we can calculate  $V_c'(t)$  as shown in Equation 1.5.

$$V_c'(t) = \frac{-x'(t) \cdot (T - t) + X - x(t)}{(T - t)^2} \quad (1.5)$$

Based on Equations 1.3 and 1.4 we can conclude that:

$$(1.3), (1.4), (1.5) \Rightarrow V_c'(t) = \frac{V_c(t) - V_u(t)}{T - t} \quad (1.6)$$

If the user always walks slower (or faster) than the controller's speed setpoint,  $V_c'(t)$  will always be positive (negative) before reaching the destination (*i.e.*, for  $t < T$ ) and this can cause problem if the user always walks slower than the speed

<sup>1</sup>Setpoint is the desired output that an automatic control system aims to reach.

<sup>2</sup>If  $f(x) = \frac{g(x)}{h(x)}$ , the derivative of  $f(x)$  is  $f'(x) = \frac{g'(x)h(x) - g(x)h'(x)}{h(x)^2}$ .

setpoint because the speed setpoint will continue to increase until the user reaches his/her maximum speed possible (*i.e.*, cannot walk faster) in which case arriving on-time will become impossible because the user's speed is not fast enough. This situation is demonstrated in Figure 1.3.

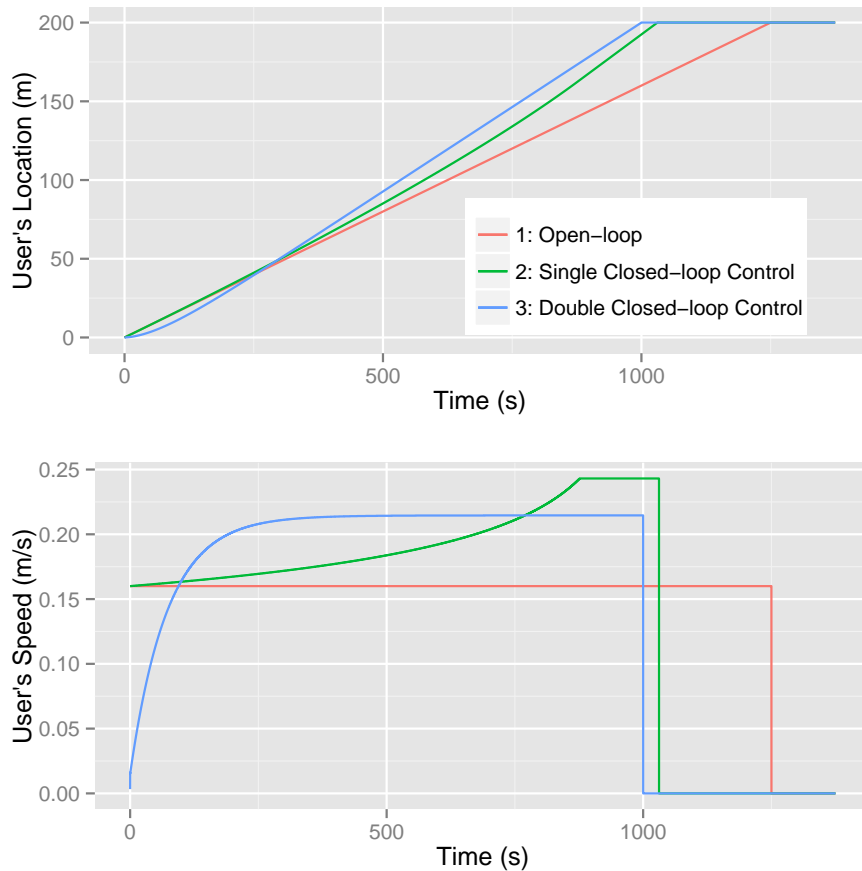
### **Double Closed-loop Control**

User error and estimation error, including the estimation of the desired cadence based on the desired speed, can easily be minimized with an additional feedback channel in the system by adding the user's estimated walking speed (*e.g.*, via GPS) as a feedback to the system as shown in Figure 1.2 (bottom); to make sure error does not accumulate, we can use a PI controller<sup>3</sup> that tries to minimize current error as well as summation of error over time. This internal loop is responsible for constantly adjusting the guidance cue until the user walks at the desired speed, even though the desired speed might be changing over time according to the remaining time and distance to destination. The blue line in Figure 1.3 shows how this setting manages to bring the user up to the desired speed before it is too late. It is worth noting that with the addition of the new feedback loop, the "short-term response" of the system actually becomes slower (*i.e.*, the gradual increase of speed under double closed-loop system in contrast with the other two in Figure 1.3), but the long-term response is superior to previous settings. It is possible to use a PID controller or to combine this setting with one of the previous ones in order to get a fast short-term response and error-free long-term response but that is beyond the scope of this discussion.

In this thesis, we have begun to explore the possibility of using Periodic Vibrotactile Cues for the fine-grained control of cadence and speed (*i.e.*, guiding a walker's cadence and speed with precision). The above control systems are just examples of a very large design space of cadence controllers that are possible, none yet tested. Our focus in this thesis is on the user's ability to follow periodic cues and the immediate challenges and requirements of a PVG system such as sensitivity

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<sup>3</sup>A Proportional-Integral-Derivative (PID) controller calculates error of a system (the difference between a measured variable and a desired setpoint) and tries to minimize it by adjusting the input to the system. The *proportional*, *integral*, and *derivative* values are responsible for reducing the current error, accumulation of past errors, and the rate at which error increases (*i.e.*, predicted future error) respectively. In many applications it is common to use just a PI controller rather than a PID controller because derivative action is very sensitive to noise and can be problematic.



**Figure 1.3:** A user's location (upper) and speed (lower) response to the PVG system in three settings: open-loop (red), single closed-loop (green), and double closed-loop, with a PI controller (blue). The user has 1000 seconds to be at a destination 200 meters away. The desired speed is thus 0.2 m/s and the user always walks 20% slower than the speed setpoint. As a result, with the open-loop system (*i.e.*, no feedback) the user arrives 250 seconds late. As Equation 1.6 shows, if the user always walks slower than the speed setpoint which is estimated based on the location of the user in the single closed-loop control system (*i.e.*, location feedback) increases the tempo of the guidance cue over time and rushes the user near the end until it reaches the user's limit (see the overshoot) but the user still arrives 30 seconds late. The double closed-loop system (*i.e.*, location and speed feedback) increases the tempo of the guidance cue based on the user's location too, but it also takes the user's departure from the desired speed into account and increases the setpoint even more until the user walks at the desired speed; as a result, before it is too late, the user gets a steady speed (slightly larger than 0.2 m/s to make up for the time the user walked slower than desired) and eventually arrives on time.

in mobile contexts, cadence estimation, susceptibility to periodic cues, workload, and auditory multitasking.

### 1.3 Research Goals

The overall goal of this thesis is to develop a new haptic guidance method (PVG) to be used in mobile contexts. In particular, we try to find the best setting for wearable vibrotactile displays with a focus on guidance of human walking, develop a robust cadence estimation algorithm, and examine users' performance and workload under PVG and the extent to which their ability to utilize it is impeded by auditory stimuli. Our aim is to answer the following questions:

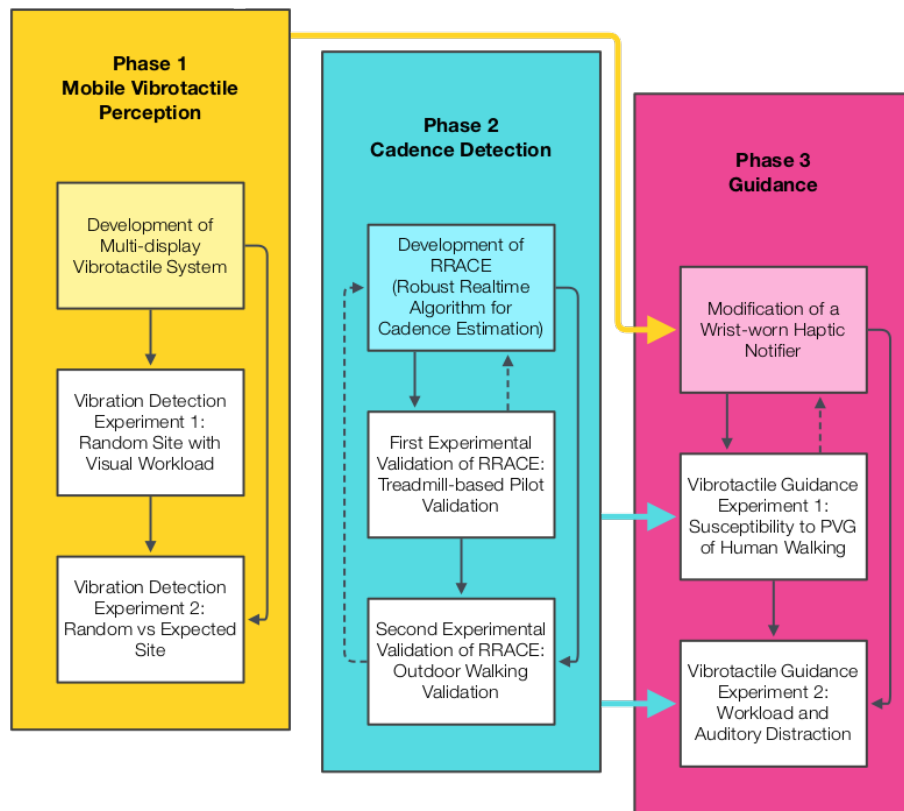
1. What is the most effective location on a user's body for placement of vibrotactile displays in mobile applications from a sensory standpoint?
2. How well can we measure cadence in realtime under a convenience-driven constraint that no *a priori* knowledge about the user is used?
3. Can walkers synchronize their step frequency with a Periodic Vibrotactile Cue?
4. How much workload does Periodic Vibrotactile Guidance cause?
5. How much do different types of auditory tasks affect walkers' performance?

### 1.4 Research Approach

This research is done in three main phases as depicted in Figure 1.4: First, we<sup>4</sup> need to find the right vibrotactile display and the best location for its placement in mobile contexts and PVG in particular. Second, we develop a cadence estimation device to be used in evaluation of PVG and eventually in the PVG control system. Finally, we study users' ability to follow Periodic Vibrotactile Cues at different rates and during auditory multitasking. In this section we will explain these phases.

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<sup>4</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.



**Figure 1.4:** The three phases of our research are shown as three large rectangles. Phase 1 (yellow): evaluation of vibrotactile stimuli under mobile conditions and finding best body locations for their placement. Phase 2 (cyan): development and evaluation of a cadence detection algorithm. Phase 3 (pink): study of performance, workload, and effect of auditory multitasking on PVG. Each phase starts with a development stage (small coloured rectangle) followed by two experiments (white rectangles). Solid arrows show dependencies between stages/phases: starting point is a prerequisite for the ending point. Dashed-line arrows show a reiteration in a development stage where the findings of an experiment (or requirements of the next experiment) dictate changes to the developed system.

### **1.4.1 Phase 1: Sensitivity to Vibrations in Mobile Contexts**

The choice of haptic display technology and more importantly, location for placement of vibrotactile display was not trivial at first. As our first step, in Chapter 2, we review the haptic channel, tactile technologies, and the way they have been used in guidance system to identify the potentials and challenges that we are facing for the development of PVG.

In Chapter 3 we compare several body locations for placement of vibrotactile displays in terms of Detection Rate (DR) and Reaction Time (RT) during walking in two experiments. In the first experiment we also measure the effect of visual workload and in the second experiment we compare vibrations on expected body locations with vibrations on unexpected body locations. Phase 1 is shown as a yellow rectangle in Figure 1.4 and is a prerequisite of Phase 3.

These are the questions we tried to answer:

1. Which body locations are more sensitive to vibrations?
2. Which body locations are more affected by movement?
3. Does visual workload impact performance?
4. Which body locations are preferred by users?

### **1.4.2 Phase 2: Cadence Detection**

The PVG system that we proposed relies on a cadence estimation unit that could measure the user's cadence with high precision and in realtime. We required the system to be small enough to be carried by users, work out of the box (*i.e.*, no tuning required), robust to user differences and placement on the body. At the time, such a solution that was available for modification as open-source software did not exist. We knew we could use a smartphone's accelerometers to detect body movement during walking. Our idea was that the main component of the frequency-domain transformation of the accelerations would belong to the cadence or one of its harmonics. In Chapter 4 we explain the development and evaluation of the resulting algorithm: RRACE. This algorithm was also the cadence measurement

instrument in the next phase of our research. Phase 2 is shown as a cyan rectangle in Figure 1.4 and is a prerequisite of Phase 3.

The main attributes of RRACE are as follows:

1. It can work across many body locations.
2. It is robust to change of orientation.
3. It works out of the box and does not require calibration.

We tested our algorithm on a treadmill and outdoors, under normal unconstrained walking conditions and examined the effect of body location and speed. We also conducted a thorough comparison between our “frequency-based” gait detection method and the highest-performing published “time-based acceleration threshold” method.

### **1.4.3 Phase 3: Study of Periodic Vibrotactile Guidance**

The goal of the final phase of our research was to verify that people can follow Periodic Vibrotactile Cues, measure the workload caused by PVG, and examine the effect of auditory tasks on users’ performance. This was done in two steps, each corresponding to a separate study; in step one we studied susceptibility to PVG of human walking, which is explained in Chapter 5. In step two, we measured workload caused by PVG and the effect of auditory task on users’ performance and workload, which is explained in Chapter 6. Phase 3 is shown as a pink rectangle in Figure 1.4; both previous phases are prerequisites of Phase 3.

These are the questions we tried to answer in this phase:

1. How well can walkers follow Periodic Vibrotactile Cue of different tempos?
2. Does repetition improve performance of walkers?
3. How much do auditory tasks of different kinds affect walkers’ performance?
4. How much workload does PVG impose on walkers?
5. Does PVG affect walkers’ stride length?
6. Does PVG affect walkers’ speed?



## 1.5 Summary of Contributions

The research presented in this dissertation makes the following primary and secondary contributions:

### *Primary Contributions*

1. Sensitivity to Vibrations in Mobile Contexts: Evidence for
  - (a) positive effect of vibration intensity on Detection Rate (DR) of stimuli and reduction of Reaction Time (RT);
  - (b) higher DR at certain body locations;
  - (c) negative effect of movement on DR and increase in RT;
  - (d) effect of visual workload on increasing of RT;
  - (e) faster RT to stimuli on expected locations versus random locations;
  - (f) gender differences in terms of DR and RT;
  - (g) subjective preferences.

These are encapsulated in guidelines for the design of wearable vibrotactile displays.

2. Cadence Detection:
  - (a) The Robust Realtime Algorithm for Cadence Estimation (RRACE).
  - (b) Evidence for performance and robustness of RRACE
  - (c) Evidence for superior performance of RRACE over the readily available state-of-the-art *time-based* cadence estimation method.
3. Study of Periodic Vibrotactile Guidance:
  - (a) A new guidance method based on fine-grained measurement of movement.
  - (b) Tactile delivery of such guidance through interval/tempo of periodic cues.
  - (c) Evidence for humans' ability to follow Periodic Vibrotactile Cues (PVCS).

- (d) Evidence for the effect of Periodic Vibrotactile Guidance (PVG) on walking speed and stride length.
- (e) Analysis of the effect of repetition on PVG.
- (f) Measurement of effect of auditory task on performance under PVG.
- (g) Measurement of workload under PVG.

### ***Secondary Contributions***

1. Experimental design, methodology, and statistical analysis examples for:
  - (a) examining sensitivity to vibrations in mobile contexts;
  - (b) measuring cadence in indoor (treadmill) and outdoor settings;
  - (c) analyzing stride frequency and length, and walking speed and workload, under guidance/no guidance and different auditory tasks.
2. Shared/open source data on:
  - (a) detection rate and reaction time to vibrotactile stimuli of different intensities across the body in stationary and mobile conditions and under visual workload or no visual workload;
  - (b) detection rate and reaction time to vibrotactile stimuli of different intensities across the body on random or expected locations in stationary and mobile conditions;
  - (c) acceleration of six body locations at different walking speeds and step frequencies with accompanied gold standard cadence measurements;
  - (d) performance under PVG and no guidance with and without auditory tasks.
  - (e) workload under PVG or no guidance with and without auditory tasks.

## **1.6 Dissertation Roadmap**

This dissertation is organized as follows:

**Chapter 2** gives a broad coverage of the literature on the haptic channel, tactile displays, and guidance systems with some of its elements repeated in the following chapters in narrower scope.

**Chapter 3** describes two experiments that examine sensitivity to vibrotactile stimuli under different conditions of movement, visual workload, and expectation of stimuli location.

**Chapter 4** presents RRACE, our algorithm for measurement of cadence in realtime and describes two experiments that verify its accuracy and robustness.

**Chapter 5** describes an experiment that examines walkers' ability to follow Periodic Vibrotactile Cues of different tempos.

**Chapter 6** describes an experiment that measures workload under PVG and the effect of auditory tasks on walkers' performance.

**Chapter 7** summarizes this dissertation and provides future directions for the research.

**Appendices A, B, C, and D** document the supplemental materials used throughout this research and associated with Chapters 3, 4, 5, and 6 respectively.

## Chapter 2

# Related Work

*If you rely only on your eyes, your other senses weaken.*  
— Frank Herbert, *Dune* (1965)

The goal of this chapter is to review guidance and explain our rationale for choosing the tactile channel for the particular guidance system that we are interested in. To achieve this goal, first, we study several guidance systems categorized by medium (*e.g.*, visual or haptic) and application in Section 2.1, define spatial, temporal, and spatiotemporal guidance in Section 2.2, and explain the benefits and drawbacks of guidance in Section 2.3. Then we review the haptic channel in Section 2.4 and tactile display technologies in Section 2.5 to explain our choice of tactile display throughout this dissertation.

### 2.1 Guidance Systems

There is a wide variety of guidance systems, with different communication channels (*e.g.*, audiovisual vs haptic), application areas (*e.g.*, object manipulation vs control of vehicles vs spatial awareness), and ergonomics (*e.g.*, stationary vs hand-held vs wearable). In the next few sections we will explain these with examples.

#### 2.1.1 Non-haptic Guidance

A large body of research is dedicated to the studying of visual and auditory guidance for object manipulation tasks. Many of these applications are related to

medicine and surgery such as image-guided breast and laparoscopic surgery, neurosurgery, and robot assisted minimally invasive surgery [45, 59, 109, 140]. Fuchs et al. developed a head-mounted display that provided visual cues during laparoscopic surgery [45], Grimson et al. developed an image-guided neurosurgery system that shows the location of instruments with regards to the Magnetic Resonance Imaging (MRI) [59], and Sato et al. used 3-D ultrasound images for the guidance of breast surgery [140]. More recently, Mourgues et al. developed a visual guidance method for robot assisted minimally invasive coronary artery bypass graft that used coronary tree model from endoscopic images which were updated in realtime as overlay images for assisting the surgeon during the operation [109].

Guidance methods can also be used in navigation. Golledge et al. outlined several hardware requirements for a Personal Guidance System (PGS) for blind users [53]. They proposed the employment of Differential Global Positioning System (DGPS) in addition to a head mounted compass. Their system would guide users by direct speech and relied on a virtual acoustic display consisting of binaural earphones that “allow features to call as if from their real location in objective space” to give a spatial awareness to blind users. In the above examples, vision and audition were the communication channels from the guidance system to users. This can be problematic in cases where users need their eyes and ears for the primary task such as looking at the road while driving or an important secondary task such as talking to someone while walking. The requirements of such tasks suggest the use of haptic channel, which is relatively free and may not compete for visual and auditory resources.

### **2.1.2 Stationary Haptic Guidance for Object Manipulation**

One of the first areas that welcomed haptic guidance was telepresence and object manipulation. The sensors and haptic displays that were put together to give the feel of presence in a remote site to the operator were used in a different way: the haptic feedback link between the operator and the remote environment was “corrupted” , as Rosenberg defined, by overlaying perceptual information to improve task operation [131]. Rosenberg introduced virtual fixtures, which were computer simulations run on several Degrees of Freedom (DOF) force-feedback displays.

The virtual fixtures would limit the user's movement like a ruler used for drawing lines but with additional advantages that came from the nature of computer simulations. His studies showed that virtual fixtures could enhance the performance of a teleoperation by 70%.

In a similar work, Bettini et al. studied the employment of both hard and soft virtual fixtures for a multi-step task of surgical tool manipulation [8, 9]. They used admittance control to develop soft and hard virtual fixtures for haptic guidance in micro and macro scales. Their tests on *Steady Hand Robot* of *Johns Hopkins University* showed significant improvement of performance of hard and soft virtual fixtures, which included higher confidence and speed of users and reduced positioning error. Soft virtual fixtures seemed to be ideal because in addition to providing high-level guidance, they let users override the method. However, Bettini's work showed superiority of hard virtual fixtures in terms of performance.

Haptic guidance has also been used in animation browsing and editing. Donald and Henle designed a system for haptic guidance of animators during motion capture data manipulation [32]. They mapped the multi-dimensional animation configuration space into a lower dimensional space of vector fields that were displayed on a six DOF PHANToM device by SensAble Technologies Inc.<sup>1</sup> (Woburn, MA, USA) [145]. These vector fields felt like virtual objects and guided animators along certain trajectories or resisted against movement towards undesired regions. They also mentioned the use of time-varying higher-order vector fields which would change in time.

These examples show how sense of touch can assist users accomplish tasks while they are visually engaged in their primary tasks. However, the display mechanisms are stationary and do not support for mobility of the user and portability of the device.

### **2.1.3 Haptic Guidance and Shared Control of Inland Vehicles**

In some other works haptic guidance is referred to as *shared control* because of the difference in approach or the point of view of researchers. According to Steele and Gillespie, shared control can take advantage of both mechanized control and

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<sup>1</sup>SensAble Technologies Inc. was acquired by Geomagic Solutions in 2012.

human abilities [153]. They developed a guidance method for land vehicles based on shared control of a steering wheel. The control agent that can be viewed as *live fixtures*, as opposed to the conventional *virtual fixtures*, exchanged power with the human user to avoid departure from the center of a road. The torque applied to the steering wheel by the system was proportional to the angular displacement from the desired steering angle which was calculated based on the lateral displacement of the car sensed by Global Positioning System (GPS). Their studies showed 50% reduction in path following error, 42% lower visual demand, but no significant cognitive load reduction. They argued that the latter was because driving is highly learned and requires minimal amount of processing load and the verbal recitation of numbers – which was used as the secondary task – did not compete over the central processing code resources with the driving.

In a follow-up work, Griffiths and Gillespie designed new experiments with obstacles in the middle of the road and audio signals to be identified by users to compare cognitive load during and in the absence of guidance [58]. They found that the guidance system helped in maintaining the performance of the primary task when a secondary task was given to the user. The presence of the secondary task reduced the performance of the non-guided driving by 20% but it only reduced the performance of guided driving by 4%.

Forsyth and MacLean developed a haptic guidance method for inland vehicles based on a predictive control method [42]. They developed two guidance methods: one based on Potential Field Guidance (PFG) [132, 133] and the other based on a look-ahead control method [36]. These methods were employed in a driving scenario where users had to drive in a curvy road while keeping the vehicle in lane and as close to the center of the road as possible. Their experiments compared these two methods with a no-guidance scenario and showed that Look-ahead Guidance (LAG) significantly outperformed the other two (*i.e.*, no guidance and PFG) in terms of smaller mean squared error from the desired trajectory. LAG also produced smaller forces than PFG and was preferred by subjects.

The haptic displays used in the above applications are not attached to the body of the user hence they are considered grounded. This limits their applicability to situations where the user is stationary on the ground or in a vehicle.

### 2.1.4 Haptic Guidance for Training

The idea of virtual fixtures evolved into virtual training in the work of Gillespie et al. [51]. Their *virtual teacher* was similar to virtual fixtures in the sense that it would facilitate task execution, but unlike virtual fixtures, the virtual teacher was present only during training phase. They simulated moving a crane and used it as their task example. During training period, the user would try virtual teacher's strategy. They argued that by showing the analytically obtained strategy to the user he/she can bypass some parts of the usual practice time. Their experiments showed that the optimal strategy could be communicated successfully to users.

Yokokohji et al. investigated the possibility of transferring skills from one person to another through a visual/haptic display [175]. They proposed several applications of skill transfer: sports (tennis, golf), calligraphy, and surgeries (laparoscopic, endoscopic, and arthroscopic). They brought up the debate about training through guidance: on one hand, guidance prevented error, which was advantageous; on the other hand however, trial and error could be very helpful for learning, which made guidance systems contradictory to the process of learning. Yokokohji et al. developed and tested five different training methods: visual cue only, visual cue and force playback, visual cue and motion playback, visual cue and hybrid playback, and visual cue and hybrid playback with inverted force. They argued that motion playback was the most promising method. However, they noted that their results were not statistically significant to derive any conclusion probably because their task example was not difficult enough.

O'Malley et al. examined haptic guidance by comparing the performance and effectiveness of training under shared control, virtual fixture guidance, and no guidance [116]. They designed a hitting target task under a second order manual control. Two masses with a spring-damper connection formed the under actuated 4 DOF system. The subject could only control two DOFs ( $x$  and  $y$  of one of the masses). Their first experiments showed performance improvement under both guidance methods with no significant difference between them. Their second experiment showed no significant advantages for the guidance methods over the practice in an unassisted mode.

The previous work was followed by Li et al., which elaborated on the negative



effect of guidance on training [94]. The study of a target-hitting task showed that subjects who practiced in the absence of shared control guidance had better performance during the actual task. It should be noted that the negative effect of shared control for training does not prove inefficiency of other haptic guidance methods that are not based on force feedback or shared control. In other words, other haptic display methods may not have negative effect on training. In addition, it is not always desired to remove the guidance method during the actual performance.

### **2.1.5 Haptic Situational Awareness Aid**

Sklar and Sarter suggested event-driven domains such as aviation as potential applications of tactile communication [147]. They emphasized on *multiple-resource theory* [171] and suggested distribution of information to haptic modality to reduce pilots' mode errors or automation surprises (failure to notice change of status). They designed an experiment to compare three modes of feedback: visual-only, tactile-only, and visual-tactile during four phases of flight different on difficulty level. Their tactile display consisted of a wristband with one tactor attached to inner wrist and another one attached to the outer wrist. The pilots who received visual only feedback showed significantly lower detection and reaction time performance. In addition, pilots assisted by visual and tactile feedback missed a few more status changes than the ones assisted by tactile only feedback during the *dynamic phase*. This was surprisingly inconsistent with *multiple-resource theory* that suggested improvement of performance because of multiple modalities. Sklar and Sarter argued that during the dynamic phase of flight, pilots required a lot of visual attention for the primary task, and visual feedback would compete over it and cause visual scanning penalties.

Following many other researchers interested in potential uses of tactile signals, Ho et al. designed two experiments to study spatial information presentation through vibrotactile signals in cars [68]. They designed a pseudo-driving simulation and asked their participants to check if they were approaching the car ahead or being approached by the car behind whenever they received a vibrotactile signal from the back or front. One of their experiments was spatially predictive, meaning that 80% of the vibrotactile signals corresponded to the same direction (*e.g.*, front

factors for the car ahead and vice versa) and the other experiment was spatially non-predictive with random direction of vibrotactile signals (*i.e.*, 50% likeliness of vibrotactile signal having the same direction as the car approaching). Subjects responded faster and more accurately to visual events preceded by vibrotactile cues of the same direction; however, the difference between the mean cueing effect of the two experiments was not significant to prove the advantage of spatially predictive over spatially non-predictive signals.

Enriquez and MacLean confirmed the harmful effect of *false positive* warning signals (false alarms) [34]. They used a throttle pedal with force feedback in a driving scenario. Subjects had control over the position of the pedal which defined the acceleration of the car. They were asked to avoid collision with another car ahead of them by controlling the speed of their own while being occupied with a secondary task of identifying objects shown on the same graphical screen. The drivers would feel pressure from the pedal when their car approached the leading car. This pressure was produced by the force feedback system as a means of warning signal. Enriquez and MacLean examined effects of error in warning signals by adding *false positives* (false alarms) and *false negatives* (misses) and found that only false positives had negative effect on the use of haptic warning signals. They argued that false positives could destroy the user's trust and willingness to use the information presented by the system.

The above papers suggest that haptic guidance can be used in event-driven situations such as aviation and transportation. In addition, most of our tasks that have temporal parameters are in fact event-driven; for example, arrival time of a bus, train, or ferry and changes in traffic patterns are important events in an urban commute. One may argue that these tasks are not as sophisticated as aviation to require assistance. However, people normally try to maximize their use of time by accomplishing their daily tasks in parallel with as many secondary tasks as possible. Situational awareness aid seems promising in these conditions too.

### **2.1.6 Wearable and Handheld Haptics and Spatial Guidance**

Skin is the largest organ that covers the whole body with a vast number of heat, touch, and pain sensors, which is a great opportunity for interaction designers if

they intend to build handheld or wearable haptic devices. Baumann et al. used an iterative low-fidelity prototyping or “physical brainstorming” to explore the potentials of *wearable* or *holdable* haptic displays for attentional cueing [6].

Navigational guidance has been an area of interest since a decade ago. Ertan et al. introduced a wearable navigation system for guidance of blind users in unfamiliar indoors areas [35]. They used a vibrotactile display consisting of a 4-by-4 array of micromotors embedded in the back of a vest to communicate stop signal or the four cardinal directions to the user. Due to the bad reception of GPS signals indoors they used infrared transceivers in the ceiling of the hallways instead for sensing the position of the user. A wearable computer in the user’s backpack was responsible for route planning.

Bosman et al. developed a wearable haptic guidance system that could be attached to both wrists of a pedestrian to guide him inside unknown buildings [11]. Although their design could be modified to help blind or visually impaired users, they claimed it to be a great match with regular users’ vision and perception of the space around them. The advantages of their haptic guidance method were its objective performance and subjective desirability. They used vibrations to indicate directions and stop signal.

Tsukada and Yasumura developed a belt with eight vibrotactile haptic displays to guide a pedestrian towards destinations, predefined locations, or valuables left behind [163]. They used GPS to locate the user and geomagnetic sensors to detect the orientation of the user. The eight vibrotactors were located around the user’s waist, four of them pointing at front, back, left, and right, and the other four pointed at between those directions. Vibration of each tactor showed a desired direction to the user. They found that subjects could feel vibrations when stopped but often failed to recognize vibrations with intervals less than 500 ms when walking. However, subjects could stop for a moment to recognize the direction of the vibration; we will explain the negative effect of movement on sensitivity to vibrations in Chapter 3. They reported subjects’ preference for receiving signals only when they were lost and not all the time. Van Erp et al. used a similar system for waypoint navigation [167]. They mapped the four cardinal and four oblique directions to vibrations on eight tactors embedded in a belt. In order to display distance to next waypoint they developed four different schemes in addition to a control con-

dition (*i.e.*, no coding of distance). Two of the schemes were based on monotonic relation between distance and tempo of the rhythm (faster tempo indicated shorter distance) and the two others were based on communicating departure, arrival, and intermediary phase by three fixed but different tempos of the rhythm. They found no significant difference between the scheme; users maintained a below normal but acceptable average walking speed. They examined the directional-only guidance in two operational scenarios too: for a helicopter pilot and a fast boat driver and the system showed to be successful despite the vibrating environments which could have blocked the perception of the vibrotactile signals.

Wearable haptics seems to be an obvious choice for spatial guidance because of the easy mapping between directions and locus of stimuli. This direct and intuitive mapping is the main reason of success for those applications. However, the temporal aspects of haptic signals can also be used for the mapping of temporal and spatiotemporal parameters which is not explored yet.

### **2.1.7 Non-haptic Temporal Guidance**

Maruyama et al. developed a personal navigation system called *P-Tour* that provided users with temporal guidance in addition to the regular map-based navigation [104]. *P-Tour* computed the nearly best schedule for visiting multiple tourist attractions based on the user's preferences and restrictions. It would find a semi-optimal solution for the modified traveling salesman problem through a genetic algorithm which would give a suboptimal subset of tourist attractions with a sub-optimal order of visiting and time of visits.

Rhythm consists of several temporal parameters such as frequency and time which can be used in temporal guidance. In [177] Zelaznik and Lantero studied the effect of spatial visual guidance and temporal auditory guidance for the execution of a repetitive circular movement. They found that withdrawal of visual guidance affected the *topocinetic* aspects (size and location) of the task but did not affect the *morphocinetic* aspects (shape) of the task. They also found that the temporal guidance of the metronome had almost no effect on the spatiotemporal aspects of the task. Their conclusion was based on high precision of subjects' mean interval duration: "the overall within-subject standard deviation was about 2.5% of

the mean interval”. One of their most important findings was that subjects could maintain the proper average cycle duration in all conditions but they needed a few cycles to get synchronized with the rhythm.

These studies support the idea of temporal guidance in two ways: (a) feasibility of temporal guidance from software and hardware development standpoint and (b) practicality of rhythmic signals and ability of users to synchronize with it. Use of vision can be questionable in situations where the user’s vision is engaged by the primary task.

### **2.1.8 Haptic Feedback in Music**

Almost all acoustic and mechanical musical instruments form a closed-loop system with the user. While the user manipulates the instrument to make sounds, the auditory and tactual channels make a feedback and close the loop. Chafe argued that these two forms of feedback were necessary to the control of sound making in music composition and vocal communication [20]. He proposed the incorporation of haptic feedback in new musical instruments to solve the problem of instrument’s *non-determinism*. He set up an experiment to test if vibrotactile feedback at the finger tip would improve the problem of an electronic French horn. This vibrotactile feedback was simply made by sending the audio output to an actuator that vibrated the controlling device. He concluded that the resulting device improved the user’s perception of the music creation.

Haptic feedback can also be used in musical motor learning, as Grindlay proposed [60]. He studied the effect of haptic guidance on percussion training by building a single axis system to record and playback rotational movement of a wrist during drumming; this system could be considered as a *spatiotemporal* haptic guidance system. He measured accuracy of users on note timing and drumstick velocity under three guidance conditions: audio only, haptic only, and audio+haptic. His results showed the superiority of audio only over haptic only, and audio+haptic guidance over the other two. He suggested generalizing audio and haptic guidance to other applications such as dance, sports, and remote medicine.

Pedrosa studied the effect of haptic guidance for helping users follow and learn drum beat percussion patterns [121]. He asked the users to follow a rhythmic pat-

tern on a device similar to an electronic drum machine under four different conditions: no guidance, visual guidance, haptic guidance, and visual+haptic guidance. The results showed no statistically significant difference among the guidance conditions. Two of the reasons discussed in his thesis are more important for us: (a) the rhythmic patterns were harder than expected for users with little or no musical background and (b) users' delay in following the rhythm and the variation in delay contributed a lot to the error even if they seem to be playing the right rhythm.

Hearing and the sense of touch are closely related. On one hand, the vibration bandwidth perceivable by the receptors in humans' skin overlaps with the range of sounds that they can hear [62, 134]. On the other hand, vibration and sound (music in particular) both have temporal parameters such as duration, tempo, and rhythm. Aside from the natural coupling of music and haptics (*e.g.*, vibrations on the body caused by loud music or touching the instrument during performance), there has been some attempt to take this relationship further. Gunther et al. introduced the idea of tactile composition and performance [62]. They designed a wearable system consisting of thirteen transducers across the entire surface of the body with most of them close to *glabrous* (non-hairy) skin to increase sensitivity. They used the standard Musical Instrument Digital Interface (MIDI) protocol to compose thirteen tactile tracks to be played on tactile displays in presence and absence of music. They held a series of concerts and collected the feedback from the audience. Users' experience was very similar to their expectation from music. For example, the audience would be surprised if a repeated pattern varied suddenly. Some of their audience also reported that it felt as if the interface was making their body move which showed the potential of using wearable tactile displays to guide movement of the body.

The applications of haptic guidance in music show how haptic guidance can also be used for temporal aspects of tasks. The papers presented above suggest the use of haptic temporal and spatiotemporal guidance where human movements are cyclical.

### 2.1.9 Haptic Communication through Rhythm

Periodic haptic signals have been used to communicate information to users. Haptic icons were introduced as a means of communicating abstract information through the sense of touch to users under visual/auditory workload. Chan et al. suggested the use of a set of haptic icons as a turn taking protocol in a collaborative environment [21]. They developed a design protocol that perceptually optimized an icon set to address the requirements for such applications: being easily learnable, detectable, and identifiable. They designed three families of icons, one of which consisted of two-tone vibrations to convey status transition and the two other families consisting of periodic icons to indicate status of collaborators (*e.g.*, in control of the device or waiting to gain control of the device) to themselves. They used the *Logitech iFeel* mice, developed by Logitech (Lausanne, Switzerland) and Immersion (San Jose, CA, USA), [96] for their studies which are capable of displaying vibrations from 0.01 to 500 Hz. Users learned all the seven icons in approximately 3 minutes, identified them within 2.5 seconds in absence of workload. In presence of workload, identification time increased to an average of 4.3 seconds which is still acceptable in many applications. In both conditions they had an accuracy of 95%.

Ternes and MacLean used the Multidimensional Scaling (MDS) method in a protocol to design a large set of haptic icons using rhythm, frequency, and amplitude as parameters to distinguish between them [160]. They defined rhythm as a “repeated monotone pattern of variable-length notes” that can be manipulated by changing the number of notes, their lengths, and the gaps between them. They suggested limiting the length of icons to 2 seconds and 4 repeats (500 ms each) with the shortest perceivable note to be 31.25 ms followed by the same length of rest. The user studies revealed that the *evenness/unevenness* (*i.e.*, regular repeating nature versus irregularities of the rhythm) could be felt distinctively. They concluded that haptic rhythms could be distinguished by note length and evenness but suggested other parameters such as melody, emphasis, and tempo to be effective too.

The above papers show the possibilities and advantages of communicating through rhythmic haptic signals; they are reliable and they give us additional de-

degrees of freedom such as note/rest length, evenness/unevenness, emphasis, and tempo. These parameters have been used in an indirect communication through abstraction of meanings. However, one may use an indirect mapping of information to these parameters which seems to be less cognitively demanding.

## **2.2 Spatial, Temporal, and Spatiotemporal Guidance**

Guidance systems can be categorized by the dimension(s) of tasks they deal with: space or time. In this section we will explain Spatial, Temporal, and Spatiotemporal guidance systems.

### **2.2.1 Spatial Guidance**

A spatial guidance system is an assistive tool that deals with tasks in *time-invariant* dynamics; *i.e.*, the guidance system is responsible for assisting the user for a task that is not explicitly dependent on time. A compass is one of the simplest and oldest spatial guidance tools. Global Positioning Systems are also spatial guidance systems that traditionally use audiovisual channels. Many haptic guidance systems [8, 34, 42, 52, 58, 131, 153], and many non-haptic guidance systems such as [53, 109] can be categorized as spatial guidance according to the above definition. These devices only deal with spatial aspects of the task such as direction and distance. If they are used in contexts where time (and eventually speed) is important, the user will have to deal with those aspects on his/her own.

### **2.2.2 Temporal Guidance**

A temporal guidance system is an assistive tool that is *location-invariant* and deals with *time-variant* tasks; *i.e.*, the guidance system is only dependent on time. Timers, alarms, metronomes, and many devices that are used to help users keep track of time, or frequency of a repetitive task are in fact temporal guidance tools for general use and with very little or no knowledge about the user's state and goals. Temporal haptic guidance systems could potentially reduce visual and auditory attention by keeping the user informed about future events only when necessary. Haptic feedback is a good candidate for this because there are many locations on the skin that are not engaged in any tactile communication and can be used in



*interrupt-based* communication [156], whereas the visual and auditory channel are busy most of the time. The option can always be open for the user to check the graphical display of the device. However, if the user trusts the guidance system's judgements, he/she no longer needs to double check the time to future events like he/she does with a clock alarm before it rings or a calendar to double check future events. In addition, a temporal guidance system can assist users in micromanagement of time. In the context of this research, micromanagement of time includes controlling movement frequency or speed and synchronization with a reference (*e.g.*, tempo of the music) or another user (*e.g.*, lead rower of a row boat).

### 2.2.3 Spatiotemporal Guidance

A spatiotemporal guidance system is a generalization of both temporal and spatial guidance because the system deals with *time-variant location-variant* dynamics [104, 159]. The guidance system assists the user in space and time. Passage of time affects spatial constraints and vice versa; *e.g.*, if the user takes longer than expected to take a bus at a certain station, the system may realize that the next best choice is another bus at a different station. A simple example of spatiotemporal guidance can be seen in [32] where the user has to follow a 3D trajectory at a certain speed.

Mobile tour guides are one of the few guidance systems that take both time and location into account [104, 159]. Maruyama et al.'s *P-Tour* computes the near-best schedule and navigation for visiting several of a tourist's destinations and modifies the schedule based on tourist's location [104]. In addition to scheduling and navigation, ten Hagen et al.'s Dynamic Tour Guide (DTG) also provides location based interpretations [87, 159]. Although there are not very many spatiotemporal guidance systems, many of us retrofit existing technology to create our own spatiotemporal guidance systems. For example, on most smartphones tapping on an address opens the GPS enabled *map* software which may also provide turn based navigational cues (spatial guidance system); a mother who has to get through a complex route/itinerary on Saturday, dropping off and picking up kids at their events at the right time, often in unfamiliar locations, may add the addresses of places she has to be to events in her phone's *calendar* application; at time of each event (*e.g.*,

dropping her son at a soccer field) she can just tap on the address and be guided to the destination.

## 2.3 Benefits and Drawbacks of Guidance

In this section we will explain some of the major benefits as well as drawbacks of guidance systems.

### 2.3.1 Benefits of Guidance

Temporal and spatiotemporal guidance have many potential benefits for their users. They can improve the overall performance, decrease the amount of effort needed for task completion, decrease the anxiety level of the user, or facilitate learning of the task.

***Decrease in Human Effort*** In order to do a task, a person uses his/her own knowledge and may acquire additional information from other sources before and during the task, then bases his/her decisions on approximate calculations about time, location, or other parameters. A guidance system can assist the user by collecting information, calculating and estimating dependent parameters, and participating in decision making to some extent. Either of these can decrease the amount of processing load required from the user to accomplish the task [58].

***Performance Improvement*** A guidance system can improve human performance in two ways: improving the information collection process qualitatively and quantitatively, and increasing precision and speed of calculations; more importantly, it executes the actual movements from the start to the end.

Firstly, guidance systems have access to sources of information that are not otherwise accessible by the user alone. Maps, GPS data, exact time of future events (*e.g.*, train, plane, bus arrivals/departures), and even the accurate traveling speed of the user at every moment are available to the guidance system through the Internet, satellites, and wearable sensors but the user has no direct access to them. This information is directly related to the user's tasks and can be used to make or change decisions. Secondly, the user has to make decisions based on approximate calculations. At best, he/she can use other devices (*e.g.*, watches, maps, schedules) to

improve precision but it takes him/her a lot of time. The guidance system however, has a built-in computation unit that takes care of calculations in a fraction of a second. As a result, guidance systems have the potential to make the decision making faster and more reliable which improves the overall performance of the user. In addition, a guidance system can increase the frequency of access to information as needed which is a luxury a user with no guidance system cannot afford.

***Decrease in Anxiety Level*** Guidance systems can lower the anxiety level by off-loading some of the user's workload. In addition, after successfully assisting the user in several occasions, the guidance system gains the user's trust. The guidance system's decisions will prove to be reliable and the user will understand that the system has alternative solutions in hand just in case the primary solution is invalidated. The user would depend on the guidance system and worry less. Bodrov introduced many causes for stress [54] and grouped them as semantic (*i.e.*, related to facts, concepts, strategies), temporal, and organizational.

*Semantic* causes for stress are:

1. subjective task complexity,
2. deficient or controversial information,
3. dangerous situations,
4. uncertain time of information presentation.

Employment of a guidance system can greatly reduce stress by removal of the above causes. The guidance system can reduce the complexity of the task by taking responsibility for parts of it. It can also help the user avoid deficient information by improving the collection and using of it directly in high precision calculations. Increasing safety is an important goal of some guidance systems which directly reduces the user's stress. The temporal and spatiotemporal guidance systems can decrease the level of uncertainty of information presentation by developing a gradual awareness about the time of future events.

*Temporal* causes of stress are:

1. time deficit,

2. high rate of information presentation,
3. increased information flow.

Guidance systems can also decrease the stress level by removal of the temporal causes of stress. They can solve the problem of time deficit by helping users accomplish tasks faster. In addition, they can reduce the rate and speed of information presentation by filtering out the non-necessary parts and using non-abstract forms of communication.

### **2.3.2 Drawbacks of Guidance**

In addition to their benefits, guidance methods have some drawbacks. Some of them are more critical because they interfere with the primary task or annoy the user. The rest hurt the performance of the guidance system and reduce its efficiency. These drawbacks and possible ways of removing them will be briefly discussed in this section.

***Intrusiveness*** Unfortunately guidance systems are no exception to the general intrusiveness problem of many devices in multitasking environments. As MacLean discussed it, in some cases the interaction with the device may just become another distraction for the user [100]. For example, looking at the screen of a GPS device after hearing an audio signal for direction can make the driver miss a road sign or an obstacle. Using the haptic channel instead of vision or hearing can reduce this effect to some extent by simply not interfering with the senses (usually being vision and hearing) that are already engaged with the primary task. However, because haptic signals can still distract users and guidance systems have a multitasking nature, haptic guidance designers should balance the level of intrusiveness of haptic signals with their priority level; an urgent signal should attract more attention from the user while a less important message should be less interrupting. More importantly, the level of attention the user needs to give to the primary task should be taken into account; if it is unsafe to distract the user from his/her primary task the system should be less interrupting [100].

***Cumbersomeness*** Because guidance systems are supposed to be carried by users all the time they should be light and small. However, guidance systems require

several pieces of hardware which can make them big and heavy. In order to avoid cumbersome one can use simple designs with minimum number of sensors and smaller parts such as miniature sensors and vibrotactile displays if possible; this will also be better in terms of lower power consumption for a device that depends on battery power for portability.

***Reliance on External Data*** Guidance systems rely heavily on external data sources such as GPS network or the Internet to acquire navigational and temporal information for planning. This makes the guidance system vulnerable to accessibility problems. When the data networks are not in range the guidance system will become unusable/unreliable unless the information is provided to them from an alternative source. Using indoors infrared navigational signals, where there is no reception, is an example of providing an alternative source of information [35].

***Sensory Adaptation*** When people are exposed to stimuli for a significant amount of time they adapt to them which means that their sensitivity threshold increases or they become less sensitive to the stimuli [23]. Most guidance systems continually send signals to users and because of that there is a likelihood that after some usage users will become less sensitive to the guidance signals. To prevent this from happening, we should avoid long periods of stimulation when not necessary. An example way of doing this in vibrotactile communication is to use as short as possible vibration cycles (which might be perceived as taps) and embed the information in the length of silence between vibrations. Of course, this is only feasible when the communication is as minimal as mapping a single guidance parameter to just one degree of freedom which is the rest (silence) between notes.

***Error Situations*** Guidance systems are vulnerable to several types of errors. The information supplied to the system can simply be wrong as a result of sensor noise, inaccuracy of measurements, or network errors. In addition to machine related errors, there are errors that happen on the user side such as misunderstanding of a signal, missing a signal, or even confusing stimuli from another source (*e.g.*, coins moving in the pocket or touching each other) with the guidance signal. Noise can be avoided by using appropriate filtering of the signal. Network errors can be overcome by repetition and minimal use of bandwidth. The errors in perception of the signal can be reduced by using better contact and choosing the right locus

of stimuli. Also, if the guidance method works based on repetitive communication (such as the proposed rhythmic method) when the user misses or misunderstands a single signal he/she can be corrected by the repetitions of the signal.

***Hindering Skills and Attention*** Guidance systems may also disengage their users from their environment [92]. By using guidance systems we stop relying completely on our own cognitive functions. Over time, those functions do not get practiced as much as before which may hinder their development and/or be lost altogether. For example, GPS devices have long been criticized for obstructing the development of cognitive maps [18].

## **2.4 The Haptic Channel**

Skin is the largest organ which is covered by a vast number of receptors that form proprioception (sense of relative position of body parts), mechanoreception (touch), thermoception (temperature), and nociception (pain). The haptic channel has advantages to vision and audition that makes it a better choice than them in some applications but has limitations which should be considered in the design of those application.

### **2.4.1 Advantages of Haptic Channel**

The haptic channel has some unique features which make it a great match for guidance systems and very advantageous according to Van Erp, Grindlay, Feygin, and many others [11, 40, 61, 163, 165, 167].

1. The haptic channel is available most of the time to receive new information.
2. It is private.
3. It can help capture and direct attent to audiovisual displays.
4. It can free the overloaded visual and auditory channels.
5. It can replace a visual display when vision is blocked (*e.g.*, firefighters in dense smoke or divers in dark waters)

6. The haptic channel can be used in environments which must be auditorially silent.

The single biggest advantage of the haptic channel is being dispersed. There are simply contexts where the convergence of mobility, attention, and other contextual factors, not only render visual and auditory modalities inappropriate, but touch can be actively preferred and more comfortable. It keeps things compartmentalized and in the background in a way that feels good and optimal.

In situations where users are overloaded with (mostly visual) information, auditory and haptic notifications can help direct their attention [39] and make them notice visual changes [158]. In contrast to peripheral vision – which can also be used for attention allocation [114] – touch and audition are *omnidirectional* (i.e., do not require a particular orientation of head) and they do not require real estate [139]. Touch is often preferred to audition because it also avoids overloading of the auditory channel, which could be occupied by alarms and conversations [39]. It is shown that the haptic channel is also capable of distinguishing the level of urgency (e.g., “ignorable” vs “demand action”) when capturing attention [179]. Capturing users’ attention selectively (with users’ priorities in mind), reducing distractions, and shortening response time is especially important in the face of the exponential increase in the amount of information presented to users in different contexts such as driving and navigation [91].

The above arguments particularly support the idea of using the haptic channel in temporal and spatiotemporal guidance when users are already occupied in a primary task which involves visual and/or aural attention or when those senses are blocked or using them is not desired in those particular environments. They also explain the increasing use of touch as an information channel in many settings as a response to the problems that arose with the increase in audiovisual information and the opportunity that haptic technologies provided [73].

#### **2.4.2 Disadvantages and Limitations of Haptic Channel**

The haptic channel has limitations and some disadvantages compared to the visual and auditory channel too:

1. Haptic wearables are intrusive and sometimes the stimulus is irritating.

2. Site availability is a problem.
3. Physiological sensitivity to tactile stimuli decreases if the body part receiving it is in motion [23].
4. Using current technology and human sensory training, the amount of information that can be transmitted is very limited compared to the visual and auditory channel [163].

However, some of these are not unique to haptic channel. For example, headphones (auditory) are also intrusive and imperfect; they can fall out of ears, they are cumbersome, social irritant, subject to interference from ambient sound, and they can even cause ear damage if over or mis-used. Yet, over the last few years they have become quite accepted socially and by individuals for public use at levels that seemed unthinkable even a decade ago. The really important disadvantage of haptics relative to vision and audition is information transmissibility, at least when defined as a “bit-rate” deliverable by current technology. We should point out that this only applies to synthetic touch; real-world touch is somewhat different.

Good application candidates for haptic channel are those which require modest information transmission and consider the other limitations.

## 2.5 Tactile Display

Stimulus display is essential to the proper functioning of a guidance system, whether open or closed loop. As mentioned in Section 2.4, haptic displays have advantages relative to audiovisual displays but they have relatively lower information transmissibility, which should be considered in the design of haptic interfaces. In this section we present several types of haptic displays and our rationale for choosing one of them.

There are two types of haptic displays: *force-feedback* and *tactile*. Force-feedback displays are bidirectional physical interfaces that exert force or torque on the input device (*e.g.*, steering wheel, joystick, mouse, etc.). While manipulating the input device, the user may feel forces that encourage or resist the movement of the device. Some examples of this type of guidance can be seen in cars: force-feedback enabled steering wheels and pedals [34, 42, 58, 153]. Force-feedback



has also been used in guidance of hand motion in surgical operations or object manipulations [8, 32, 131]. The *PHANToM* haptic device from SensAble is the most common haptic display in these applications [145]. These devices should be grounded to be able to exert forces to the user. Because force-feedback devices require physical grounding – and also tend to have significant power needs – they are less appropriate for mobile applications.

Another emerging subgroup of force-feedback displays is exoskeleton force-feedback systems [7, 12, 44, 63]; these are wearable haptic devices with limbs and joints that wrap around parts of the user’s body and exert forces as the user moves his/her limbs. Among these, exoskeleton force-feedback for fingers such as the *Rutgers Master II* [12] has potential for mobile applications if it can be made sufficiently lightweight and power efficient, because instead of being grounded it can be fixed to the user’s body. The force-feedback display modality that seems like a serious candidate for a mobile applications is pressure display (*e.g.*, a compressive wristband) such as Baumann et al.’s *ServoSqueeze*, a wristwatch band that employed a micro-servo motor to emulate the sensation of being squeezed [6].

Tactile Displays are unidirectional physical interfaces that employ vibrations [166, 180], tapping [6], twisting or stretching of the skin [98], compressing of the skin, and indentation to convey messages to users [118]. Unlike the force-feedback displays, tactile displays are not necessarily collocated with the input device and need not be grounded. These two characteristics make them suitable for portable and wearable devices that can be carried by users. Users can hold these devices in their hands, keep them in their pockets, put them on, or even feel them whenever they touch the device in their environment.

In this dissertation we restrict our focus on ungrounded displays, such as tactile, because the Periodic Vibrotactile Guidance (PVG) has to be portable and does not require bidirectionality. In the next section we discuss tactile display technologies.

### **2.5.1 Technology**

Tactile displays can be put into different categories based on the kind of deformation to the user’s skin (*e.g.*, tapping, vibrating, pinching, squeezing, and twisting) or the technology they use [14, 50]; here, we use the latter categorization because

the focus of this research is on periodic cues and the user's susceptibility to them rather than perception of each single stimulus:

1. Eccentric-mass factors
2. Voice coil speakers
3. Piezoelectric speakers
4. Pneumatic vibrators
5. Electrotactile displays

From among these, voice coil and piezoelectric speakers and eccentric-mass factors are most commonly used for the development of tactile displays.

Eccentric-mass factors are widely used in consumer electronics and handheld devices in particular. One way to produce mechanical vibration is by rotating an *off-centered* weight. These displays commonly known as *eccentric-mass factors* or buzzers consist of a small motor with an off-centered weight attached to its shaft. When the motor is running, the centrifugal forces make the whole body of the display vibrate at the frequency of the motor; this means that the vibration frequency and amplitude of the eccentric-mass factor cannot be changed independently. Another way of producing vibration or tapping is to move, push, or stretch the skin.

Voice coil and piezoelectric speakers are also common in wearable haptics community but not as widely used in consumer electronics as mechanical vibration. Same as eccentric motor vibrators, both above types of displays are inexpensive, compact, and easy to control. Voice coils have an extra advantage too: they can provide a range of frequencies [62].

### **2.5.2 Degrees of Freedom**

Apart from their portability advantages and in spite of their simplicity, vibration and tapping mechanisms have much potential for employment in the context of guidance systems. These mechanisms provide several Degrees of Freedom [14, 118, 165] some of which are correlated:

1. Amplitude of vibration/tapping

2. Frequency of vibration
3. Rhythm (note density, number of notes and rests and their length)
4. Location of stimuli
5. Tempo of a rhythm or time interval between single vibrations/tappings
6. Duration of vibration
7. Duration of silence

These parameters can be used to communicate different types of temporal and spatiotemporal information to users.

**Frequency and Amplitude:** Humans' skin is sensitive to a bandwidth of 700 Hz [134]. Our ability to analyze vibration frequency is very limited. Rothenberg et al. found that people can differentiate seven levels of vibration frequency in the clearest region of sensation (80 – 90 Hz) with their forearm and up to ten levels with their fingers [134]. Other papers reported slightly different results. For example, Gunther et al. reported that humans could perceive vibrations from 20 Hz to 1000 Hz with the maximum sensitivity at 250 Hz [62]. The inconsistency of psychophysical parameters (frequency in particular) among different papers is because of the dependency of the results on the stimulation medium and the locus of stimulation. Sherrick investigated the interaction between frequency and amplitude and found when frequency and amplitude are co-varied redundantly, people could differentiate more levels (5-8) than when amplitude was constant and only frequency varied (3-5 levels) [146]. However, as Sherrick discussed, the designer should be cautious as low frequency at high amplitude could be confused with moderate frequency at medium amplitude.

**Rhythm:** Similar to music as a particular form of aural stimuli, tactile stimuli have a rhythmic characteristic. Number of notes and their timings in a repetition can form different rhythms. Swerdfeger et al. performed a set of studies which showed that rhythmic differences (*i.e.*, evenness/unevenness) dominate other parameters in terms of being perceived by humans [155]. Intensity differences (co-variation of frequency and amplitude) came right after rhythm.

**Location of Stimuli:** The vast number of touch sensors in the skin that covers the whole body gives us another parameter to use in haptic communication: location of stimuli. An interaction designer can place vibrotactile displays on both wrists of a user to distinguish left and right and create other messages as in the work of Bosman et al. [11]. Alternatively, eight vibrotactile displays at the four cardinal directions and the four intermediate directions around the waist [163, 167] or an array of vibrotactile displays on the user’s back [35] can communicate direction.

**Tempo of Rhythm:** Similar to rhythmic music, periodic vibrotactile cues have a tempo that can be used for mapping of continuous variables such as time or distance. For example, faster tempo (*i.e.*, shorter interval between vibrations) can convey shorter time or distance to a destination [167].

## 2.6 Summary

There are many examples of haptic and non-haptic guidance systems. Most of them are spatial and very few are temporal or spatiotemporal guidance systems. Despite the fact that one of the greatest potentials of the tactile sensation is its temporal aspects such as rhythm and tempo, it is not employed very often in temporal, and particularly spatiotemporal guidance systems. To the best of our knowledge, tempo of a cue (auditory or tactile) *as a fine-grained control method* has not been used or suggested for any temporal or spatiotemporal guidance system. We believe Periodic Vibrotactile Cues can be used in spatiotemporal guidance of human movement. As we discussed in Section 2.5, our ability to distinguish between vibration frequencies is very limited and frequency of vibration is not a good fit for the fine-grained guidance that we are interested in. Therefore, eccentric-mass tactors, which are cheaper and more powerful than piezoelectric and voice-coil speakers, are our tactile display of choice throughout this work.

## Chapter 3

# Detecting Vibrations Across the Body in Mobile Contexts

*Touch comes before sight, before speech.  
It is the first language and the last, and it always tells the truth.*  
— Margaret Atwood, *The Blind Assassin* (2000)

In this chapter we<sup>1</sup> explore the potential and limitations of vibrotactile displays in practical wearable applications, by comparing the user’s detection rate and response time to stimuli applied across the body in varied conditions. We examine which body locations are more sensitive to vibrations and more affected by movement; whether visual workload, expectation of location, or gender impact performance; and if users have subjective preferences to any of these conditions. In two experiments we compare these factors using five vibration intensities on up to 13 body locations. Our contributions are comparisons of tactile detection performance under conditions typifying mobile use, an experiment design that supports further

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This chapter appears with minimal modifications in [78]:

- I. Karuei, K. E. MacLean, Z. Foley-Fisher, R. MacKenzie, S. Koch, and M. El-Zohairy. Detecting vibrations across the body in mobile contexts. In *Proceedings of the 2011 annual conference on Human factors in computing systems - CHI 11*, pages 3267-3276, 2011

<sup>1</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.

investigation in vibrotactile communication, and guidelines for optimal display location given intended use.

### **3.1 Introduction**

Graphical and auditory interfaces prevalent today are information-dense, but also lead to problems such as perceptual overload and inefficiency of the visual and auditory channels [70, 162], decline in primary task performance from secondary task competition for perceptual resources [163], and situations where vision and/or audition are unavailable or inconvenient [167]. In mobile environments, phones, GPS guidance tools, and music players contribute to sensory resource starvation, where vision is heavily occupied, and auditory channels are compromised by external noise and social concerns. Tactile display is seen as a promising conduit for mobile communication, lacking the drawbacks of visual or auditory display; but it brings its own challenges. Vibrotactile displays embedded in a handheld device can notify users, without visual load and in private or noisy situations. However, the device must be held in the hand (a condition incompatible with the secondary or monitoring tasks that typically trigger such alerts) or stowed close to the skin. Tactile sensitivity varies widely by body location [73, 90] and with movement [124]; many users have experienced this variance with missed calls and messages. This flaw undermines the whole notion of mobile tactile notification.

One solution is for users to wear a tactile display driven through a local body network, which can then be located to optimize tactile communication rather than access to an associated graphical display. With this distributed approach, bodily location of the tactor becomes a design parameter which we do not adequately understand. Local skin sensitivity is critical, but so is context of use, convenience, appearance, and sometimes the tactor technology; some sensitive body regions are impractical for reasons of mobility and wearability. In the absence of a single correct answer, designers need guidelines based on the relative perceivability of body sites under conditions that typify mobile contexts. Of particular interest are bodily movement, for its known impact on sensitivity; and visual workload, for possible mental-resource competition.

The present experiments were constructed to inform such guidelines. While

some of the needed data exist, gaps and disparate sources make comparisons difficult.

We aimed to systematically address the questions of

(a) which body locations are more sensitive to vibrations and

(b) which are more affected by movement;

and whether

(c) visual workload,

(d) gender, or

(e) expectation of location impact performance;

and if

(f) users subjectively prefer any of these locations.

***Our specific contributions are:***

1. Comprehensive assessment of the effect of all of loci, movement, and expectation on detection probability;
2. An experiment design that can be replicated to answer more questions about vibrotactile communication; and
3. Compilation of our results into design guidelines for optimal display location for a given purpose.

### **3.1.1 Approach**

We conducted two experiments. The first, Experiment 1, varied factors identified in research questions (a-d) with stimuli applied in a random and unanticipated sequence; Experiment 2 varied expectation (e). For Experiment 1, we chose 13 body sites based on practicality for wearable use; Experiment 2 employed the 9 most promising of these. Experiment 1 varied body site, movement (sitting or walking on a treadmill), presence or absence of visual workload, and signal intensity (5 levels), counterbalanced by gender. Experiment 2 also varied expectation of stimulus

site in place of workload. A trial consisted of a single vibration at a single site. We measured the subject’s response time and logged undetected stimuli, and collected subjective preferences. A statistical analysis informed our guidelines.

## **3.2 Related Work**

In recent years, tactile displays (individual elements are known as “tactors”) have emerged from specialized uses to become accepted consumer gadgetry, with innovation in size, power use, and controllability. Vibrotactile variants (piezo and eccentric-mass tactors are most common) tend to be lowest in cost and power needs and most deployable; designers are already embedding tactors in clothing. A substantial body of psychophysical and design research exploring tactile sensitivity and wearable potential exists; here we highlight the most relevant works.

### **3.2.1 Sensitivity to Vibrotactile Stimuli**

#### ***Spatial Location***

Considerable research has examined sensitivity of particular body locations to vibrotactile stimuli. One of the most recent and comprehensive is Jones and Sarter’s review compilation of the effect of vibrotactile stimulus frequency, duration, intensity, and locus on detection [73]. They present sensitivity thresholds of many body locations of interest at different frequencies, and suggest ideal ranges of frequency that are most perceivable by humans. Most commercial vibrotactile displays already work within these frequency and intensity ranges.

Lederman and Klatzky provide a research summary on haptic perception. The research cited here is based on two-point and point-localization threshold methods to compare the sensitivity of different body locations [90]. While completely appropriate for the design of closely-spaced tactor arrays, these methods are mismatched to a large class of mobile contexts. For single-tactor displays (*e.g.*, held or worn cellphone), users do not identify exact vibratory location or spatial pattern; relevant metrics are likelihood and speed of detection and response. Furthermore, consumer-grade vibrotactile display diameters exceed the body’s largest point-localization threshold (*e.g.*, back).

Hoggan et al. used consumer-grade vibrotactile displays in a handheld device



and compared location recognition of vibration on fingers under different stationary conditions [70], with promise for loci and rhythm for encoding information. However, two factors that remain unexamined in a practical context are (a) movement and its interference with other factors and (b) expectations about stimulus locus.

### ***Movement***

Studies connecting movement to tactile sensitivity have involved animal and human models, and vibro- and electrotactile stimulation. For example, Chapin and Woodward found suppression in movement conditions in SI<sup>2</sup> cortical response of rats to electrical stimulation through electrodes implanted in the forepaw, when comparing treadmill locomotion, spontaneous grooming, quiet resting and “tensed-up” mobility [22].

Using electrotactile stimulation on the forefingers of human subjects, Angel and Malenka [3] found correlations between sensory suppression and movement speed in detection rates. In a similar experiment, Chapman et al. found that both active and passive movement of the ipsilateral arm increased the detection threshold by 50% on the mid-ventral aspect of the right forearm [23].

Post et al. studied the same effect but with vibrotactile stimulation [124] on the operant arm (forearm, thenar eminence, and distal digit) under different motor activity levels. Voluntary motor activity increased the vibrotactile detection threshold. The above papers consistently indicate that body motion directly affects the detection of vibro- or electrotactile stimuli. However, none compare relative vibrotactile sensitivity by site, for activities of interest here such as natural walking.

### **3.2.2 Wearable Haptic Systems**

Bosman et al. developed a dual-wrist system to guide a pedestrian inside an unknown building; vibrations indicated directions and stops [11]. Although their design could help blind or visually impaired users, it was intended to augment unimpaired space perception, and improved performance. In a different strategy, Rukzio et al. developed a guidance system based on the single palmar vibrotactile phone display and a public display with 8 lights [136]. The lights toggled in a

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<sup>2</sup>The primary somatosensory cortex

rotation, while the phone vibrated when the public display direction matched the user's route direction. Tsukada and Yasumura developed a belt with eight vibrotactile displays distributed evenly around the waist to guide a pedestrian towards destinations, given realtime user location and user orientation [163]. Subjects felt vibrations when stopped; but when walking, often failed to recognize vibrations with intervals less than 500 ms, and stopped to assess it.

Driving support systems are natural targets for body-situated guidance and alerts. Ho et al. examined spatially informative vibrotactile signals in a driving simulation where front vs back stimuli might indicate direction of an oncoming car [68], and found promise for encoding directional information to locus of stimuli. Meanwhile, Straughn et al. compared auditory and tactile pedestrian warning systems for drivers, finding two vibrotactile displays on the driver's biceps more effective than auditory signals [154]. For short Time to Collision (TTC), the warning signal was best utilized to generate a reactive motor response (warning direction = safe direction), whereas for long TTC, attention is best served with warning = hazard direction.

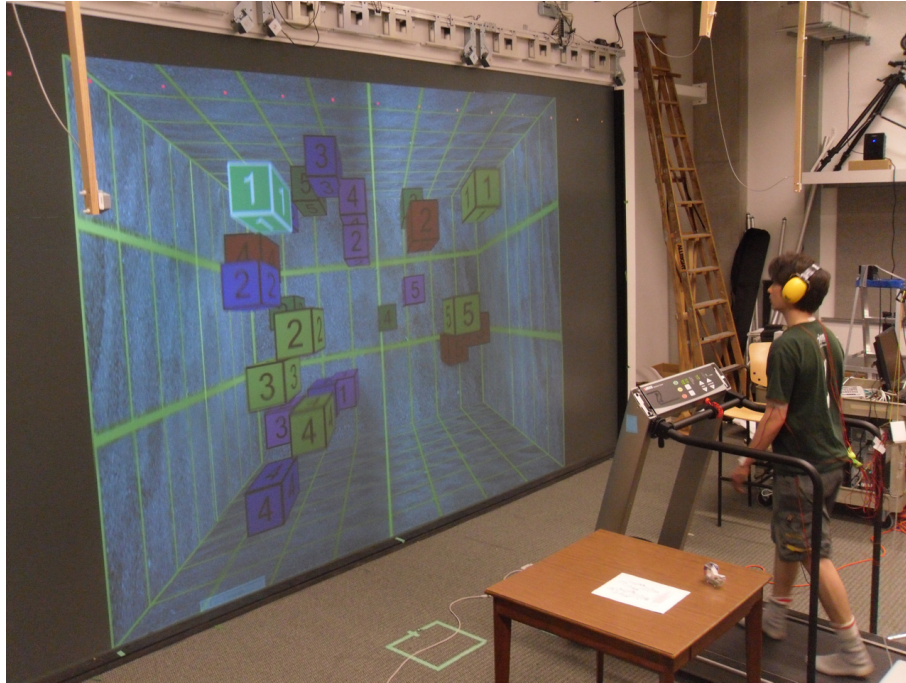
In summary, numerous tactile display setups have been prototyped; these, and others featuring back and arm. Their use confirms reduced performance during movement, which might however be confounded with workload. To our knowledge, relative site sensitivity has not been systematically explored in mobile contexts.

### **3.3 Apparatus and Setup**

Our setup consisted of a tactor array, a treadmill, a tall chair, and a large-screen display, which were deployed to create the conditions described below (Figure 3.1).

#### **3.3.1 Vibrotactile Array and Calibration**

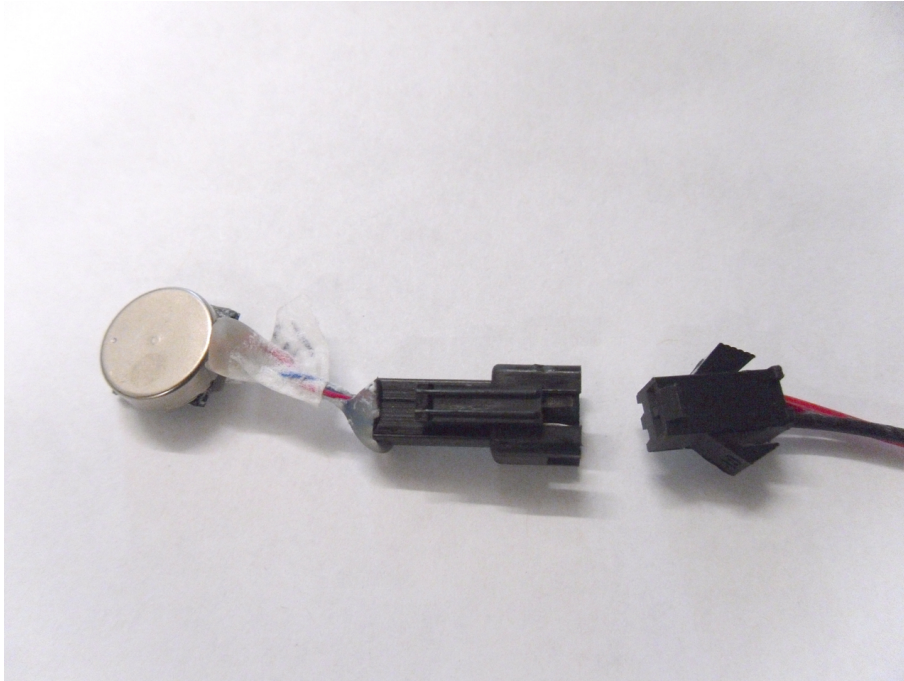
We built an array of tactors of which different subsets could be activated (Figure 3.2), with inexpensive VPM2 eccentric-mass tactors from Solarbotics Ltd. (Calgary, AB, Canada) [152], 12 mm in diameter and 3.4 mm thick. A Duemilanove Arduino processor, developed by Smart Projects Srl (Strambino, Italy), [149] drove a tactor drive circuit with quick release connectors. Resistor networks



**Figure 3.1:** Setup of Experiment 1 during “walking with visual workload” condition. Tall chair is not shown.

and Darlington transistor arrays provided 80 mA at 3 V to each motor (Figure 3.2).

The tactors were energized with Pulse-width (PW) modulated signals. To maintain resolution despite variable site sensitivity but without concern for discriminability, we specified five intensity levels spanning all site detection thresholds. We performed an iterative perceptual calibration in which we recorded pilot-subject detection rate, beginning with a logarithmic PW distribution and adjusting it to achieve satisfactory perceptual separation. To check for inter-unit variability, we measured the output of all the tactors used with a piezo-electric accelerometer (PCB Inc) aligned normal to the eccentric mass rotation plane and sampled at 5 kHz, with the tactor restrained by a magnetic mount screwed onto the clamped accelerometer. A Welch power spectrum analysis on 20 s samples indicated frequency varied by 16% (*mean* = 190 Hz, *SD* = 30), and power by 5% (*mean* = 59.0 dB/Hz, *SD* = 2.87). We addressed this variance by placing tactors on body sites with a different random layout for each participant.



**Figure 3.2:** VPM2 eccentric-mass factor.

### **3.3.2 Movement Setup and Task**

The sitting and walking conditions were chosen as typical and distinctive movement states in wearable contexts. For the former, participants sat in a tall chair for a consistent screen view. When walking, participants chose a comfortable treadmill pace that they could maintain for twenty minutes. The mean speed chosen was 2.4 Km/h ( $SD = 0.5$ ).

### **3.3.3 Visual Workload Setup and Task**

During trials with visual workload, participants sat and walked approximately two meters from a simple geometric scene on a 3(H)  $\times$  4(W) meter display (Figure 3.1). The scene showed twenty-five red, green, blue, yellow, and pink blocks in equal quantities, each numbered between 1-5, bouncing slowly around a three-dimensional room. Participants were asked to count the times a single highlighted block hit any walls in the room, including the invisible wall represented by the

screen. This task was chosen as controllable continuous visual workload characteristic of a pedestrian’s everyday attention and memory tasks, but not so distracting that participants were liable to stumble. The collision count was meant to reproduce the mental activity of a pedestrian keeping track of nearby cars and pedestrians. The other blocks simulated local objects that are distracting but need not be tracked.

### 3.3.4 Metrics and Analysis Technique

Our primary metric to assess site sensitivity as a function of condition was number of detected vs missed vibrations or Detection Rate (DR); we also used Reaction Time (RT) as a secondary indicator. Because detection data are distributed binomially, we statistically analyzed Detections with a Generalized Linear Mixed Model (GLMM) using “R” and the glmmML package [16]. We refined the model with backwards selection, beginning with many terms then iteratively removing those with the largest p-value until all the terms had significant p-values ( $p < 0.05$ ). Only main effects and significant interactions are reported.

The presence of missed-stimuli trials prevented a normal RT distribution and use of ANOVA. We replaced the censored data points (missed trials) of RT with a “sufficiently” large value and used a Kruskal-Wallis analysis, which uses metric rank rather than value to compute a test statistic. The value chosen for censored data points then needs only be larger than the maximum; we set  $RT_m = 3500$  ms for “miss” trials.  $RT_m$  renders RT means meaningless for conditions with many miss trials, which are common at low amplitudes for some body sites. Therefore in graphical comparisons of RT (but not DR) between conditions, we focus on high intensity stimuli with their higher detection rates. We also ran the Kruskal-Wallis test on the high-intensity subset, which were detected at  $\geq 98\%$  for all factors except intensity; and on the “all detected” subset for intensity, to confirm that the results are not simply due to the missed data points.

## 3.4 Experiment 1: Random Site With Visual Load

In our first pass (Experiment 1), we tested potentially relevant body sites at five amplitudes while addressing initial experimental factors of visual load and movement.

We balanced gender to allow the consideration of its impact, which could arise through, for example, gender-linked differences in body fat composition. Specifically, we examined the following hypotheses:

**H1** Intensity increases DR and decreases RT.

**H2** Body sites will differ in terms of DR and RT.

**H3** Movement decreases DR and increases RT; and it affects different body sites to different degrees.

**H4** Visual workload decreases DR and increases RT.

**H5** Gender differences in DR and RT exist.

### **3.4.1 Design**

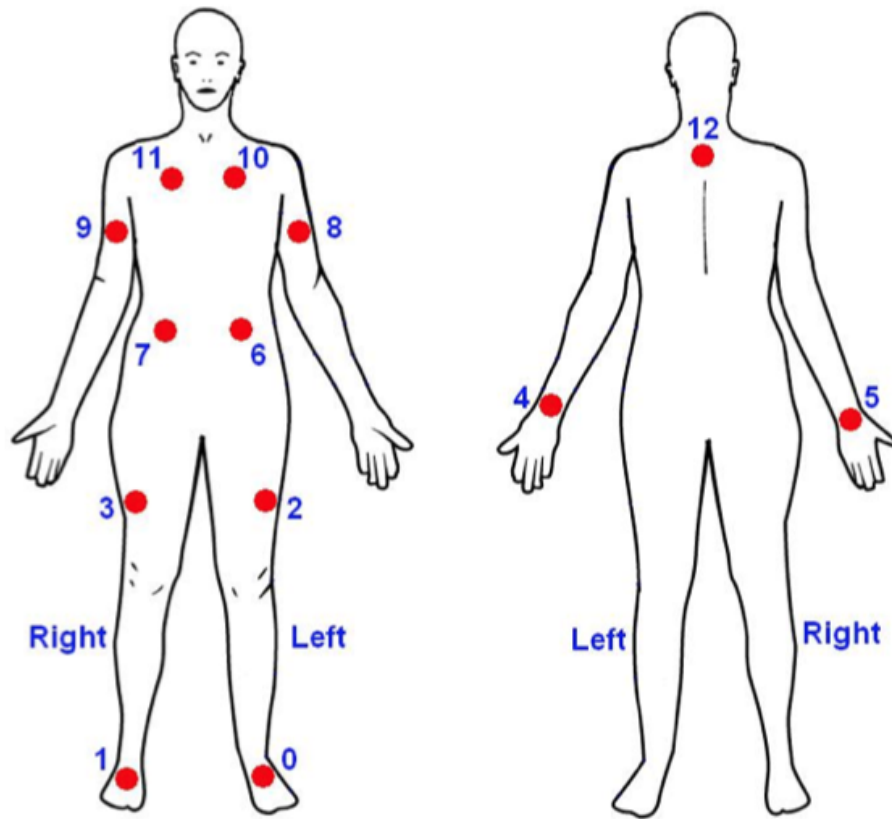
Experiment size imposed a limit of 15 tactor sites. We chose seven sites corresponding to common or potential wearable locations, and mirrored these to address possible response assymetry (Figure 3.3 and Table 3.1). 500 ms vibrations were presented in randomized order across the body sites. Per condition, each intensity was displayed twice at each right and left site, or four times at the spine.

Half the male and half the female participants first sat in a chair and subsequently walked on a treadmill, while the other half walked first then sat in a chair. During half of the walking and half of the sitting trials, we asked participants to direct their attention to the visual scene, which was turned off during the other trials.

Using a full-factorial design, we ran  $5 \times 4 \times 7 \times 2 \times 2$  (intensity  $\times$  repetitions  $\times$  site  $\times$  movement  $\times$  visual workload) trials, for a total of 560 trials per participant.

### **3.4.2 Procedure**

After signing consent forms, participants changed into sports clothing. We attached tactors (which vibrated normal to skin without slip or shear) directly to the skin at defined locations with Lightplast Pro sports tape. Except for the feet (tactors covered with socks but no shoes), no clothing covered the tactors. The interval between tactor vibrations was randomized to between four and six seconds, with



**Figure 3.3:** Body sites used in Experiments 1 and 2; sites 6, 7, 10, 11 were omitted in Experiment 2.

interval length doubled on random trials (odds of 1 to 7) for a more arrhythmic pattern. We asked participants to press the right button on a modified computer mouse when they detected a vibration. We recorded RT up to a cutoff of 3500 ms, noting missed responses. No feedback was given to responses.

Training conducted before experiment trials:

1. Experience maximal vibrations on each site.
2. Experience each of the five intensities on the wrist.
3. Respond to ten maximal vibrations at random sites.

**Table 3.1:** Body sites used in Experiment 1. ‘\*\*’ indicates sites used in Experiment 2.

Body site	Number	Location
Foot*	0,1	top surface of the foot, <i>e.g.</i> , tongue of a shoe
Thigh*	2,3	outer thigh, halfway between knee and hip joint, <i>e.g.</i> , hem of shorts on the sides
Wrist*	4,5	posterior between small bones, <i>e.g.</i> , watch face*
Stomach	6,7	halfway between navel and hip bone, <i>e.g.</i> , belt or waist band
Upper arm*	8,9	halfway between shoulder and elbow on the sides, <i>e.g.</i> , arm band
Chest	10,11	below collar bone, <i>e.g.</i> , necklace or shirt collar
Spine*	12	four centimeters below C7 vertebrae

- Count ten wall collisions in the visual task.
- Respond to ten maximal vibrations in four conditions: Sit+No Workload, Sit+Workload, Walk+No Workload, Walk+Workload.

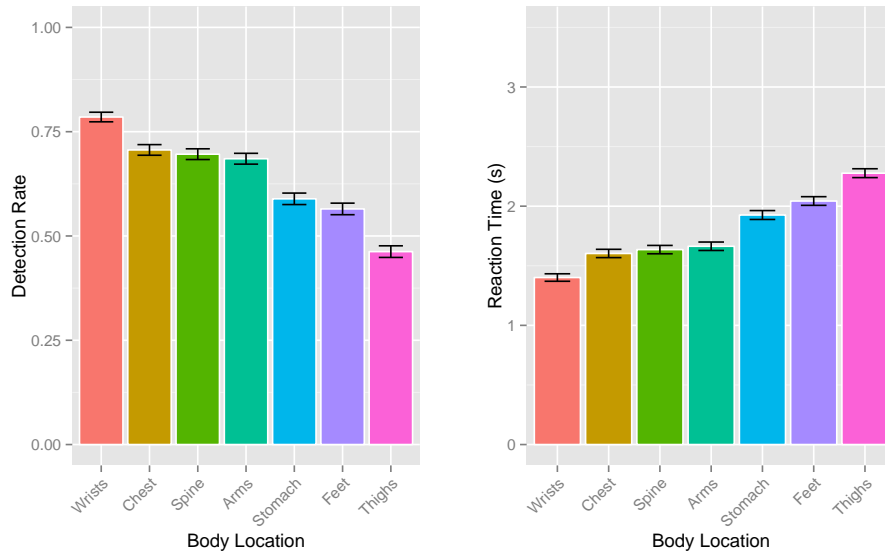
Experiment: Respond to 140 vibrations (location  $\times$  intensity  $\times$  repetitions) in four conditions, order counterbalanced by participant.

Participants took a short break after each condition and a longer break before switching movement state. After training, between conditions, and at experiment end, tactor function was verified. Participants answered online survey questions between sitting and walking conditions and at experiment end. During trials, participants wore noise canceling headphones. Sessions lasted 90-110 minutes.

### 3.4.3 Results

For this experiment, 16 participants (8 male) volunteered. These were distributed in age as 18-25 ( $n = 12$ ), 31-40 ( $n = 2$ ) and 40-60 ( $n = 2$ ); in height as tall ( $n = 8$ ), average ( $n = 3$ ) and short ( $n = 5$ ); and body type as ecto ( $n = 6$ ), meso ( $n = 7$ ) and endomorph ( $n = 3$ ). In the prior year, participant use of portable devices with tactile feedback was distributed as daily ( $n = 10$ ), 2-3 times/week ( $n = 4$ ), and  $<1$  time/week ( $n = 2$ ). Participants used a treadmill  $\leq 1$  time/month ( $n = 14$ ) and 1





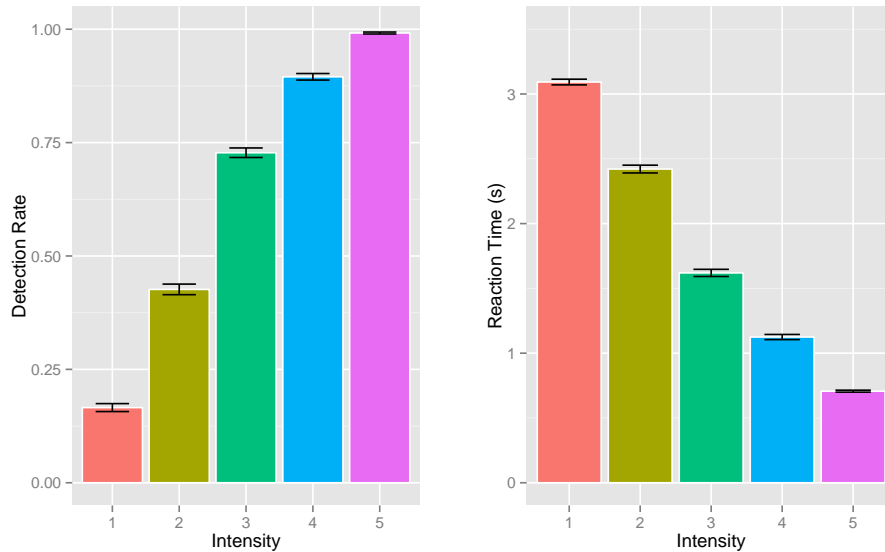
**Figure 3.4:** Mean Detection Rate (left) and Reaction Time (right) per body location in Experiment 1.

time/week ( $n = 2$ ). All reported themselves righthanded.

### Detected/Missed Stimuli DR

Intensity initially had a nearly linear effect on the estimated odds ratio of DR in our GLMM model. Therefore, we considered it as a continuous variable to increase model readability, causing only slight differences in estimates and corresponding p-values for other covariates. Finding no differences between sides, we merged left and right body sites except for spine. Feet are the baseline for sites, male for gender, sitting for movement, no workload for workload, and first trial for trial number.

In the GLMM results (Table 3.2), p-value indicates effect significance ( $p < 0.05$ ). For a significant  $p$ , a negative *coef* decreases and a positive *coef* increases odds of detection, *i.e.*, the quotient of the probability of detecting ( $p$ ) and missing ( $1 - p$ ) a signal, *i.e.*,  $p/(1 - p)$ . The odds ratio of a particular factor (*e.g.*, wrist in Table 3.2) is the ratio of the odds of detection under that condition (*e.g.*, wrist) to the odds of detection under the reference condition (*e.g.*, foot). There were very

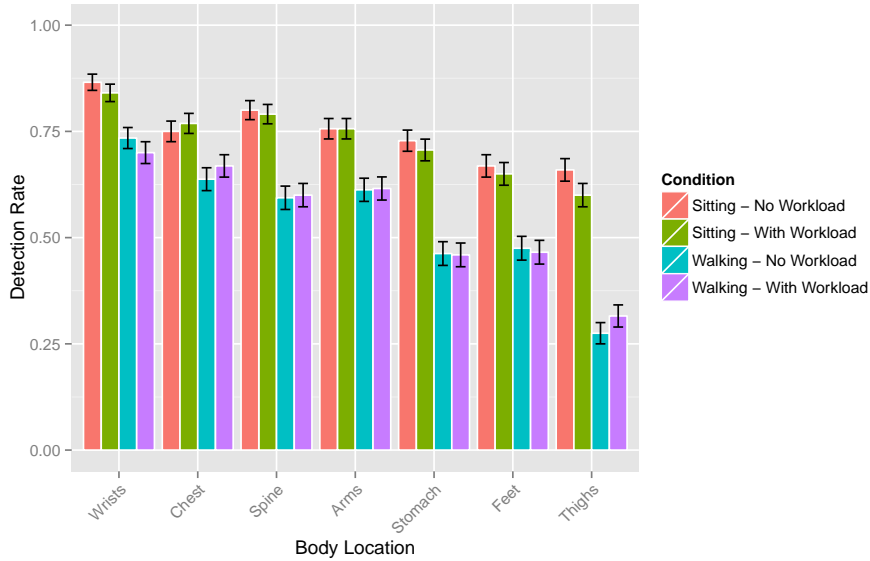


**Figure 3.5:** Mean Detection Rate (left) and Reaction Time (right) for different intensities in Experiment 1.

few false positives (1.2%), therefore we neglected their effect in the analysis.

**Main effects:** As we can see in Table 3.2 and Figure 3.4, all body sites except thighs are significantly different from feet. In terms of detecting vibrotactile signals, thighs are as bad as feet; stomach, chest, and arms are slightly better; wrists and spine are best. Walking greatly decreases odds of detection. Intensity has a significant effect (Figure 3.5), as is expected. Gender and the presence of the visual task do not have a significant effect on detection of vibrations. Trial number, which accounts for the opposing differences caused by learning and fatigue, is marginally significant ( $p = 0.048$ ). Since its coefficient is very small ( $-5.7E - 4$ ), we computed the odds ratio of detecting a vibration after 100 trials as ( $\exp(\text{coef} \times 100) = 0.94$ ); *i.e.*, the odds of detecting a vibration decreases by 6% after 100 trials, suggesting minimal practical impact.

**Interactions:** Several factors interact with body sites. By Gender: females detect significantly more vibrations on their thighs. By Intensity: higher intensity



**Figure 3.6:** Mean Detection Rate per body location and condition in Experiment 1.

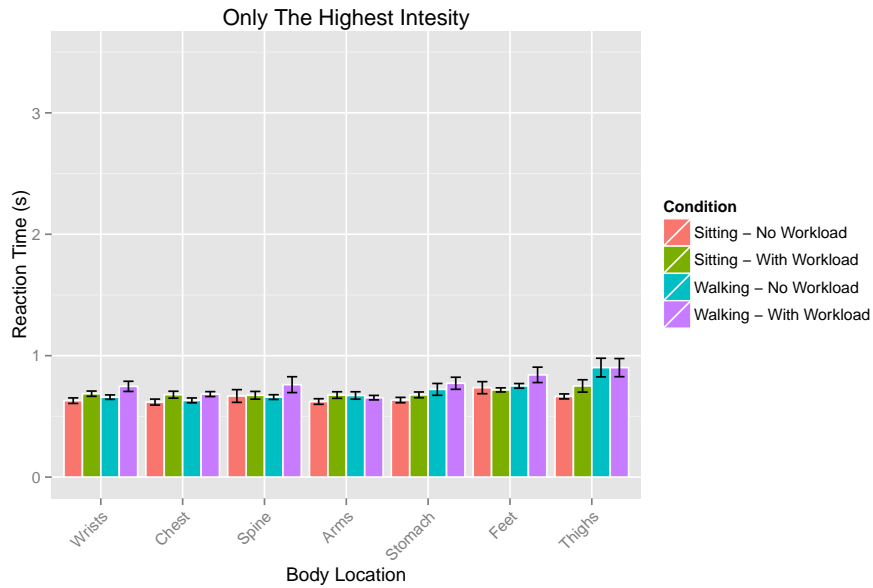
increases detection on spine, arms, wrists, and stomach less than other sites, with spine the least sensitive.

For all sites except spine and stomach (*e.g.*, Wrists:Walking), Movement decreases DR but it affects chest, arms and wrists least (Figures 3.6 and 3.8). The positive coefficients for interactions between Movement and these body sites do not compensate for the negative main-effect of movement coefficient.

### Reaction Time (RT)

We ran two sets of Kruskal-Wallis tests for RT: on the entire dataset, using 3500 ms for missed vibrations, and on a data subset containing only high-intensity trials where most of the vibrations (99.2%) were detected. Both sets show that Intensity, Site, Movement and Task have a significant effect on RT, but gender and trial ID do not (Table 3.3). Intense vibrations are detected faster (Figure 3.5), and movement and visual workload increase RT (Figure 3.7).

We also ran the Kruskal-Wallis test on Intensity for only the trials that were detected (excluding *misses*), finding a significant effect of Intensity on RT ( $p <$

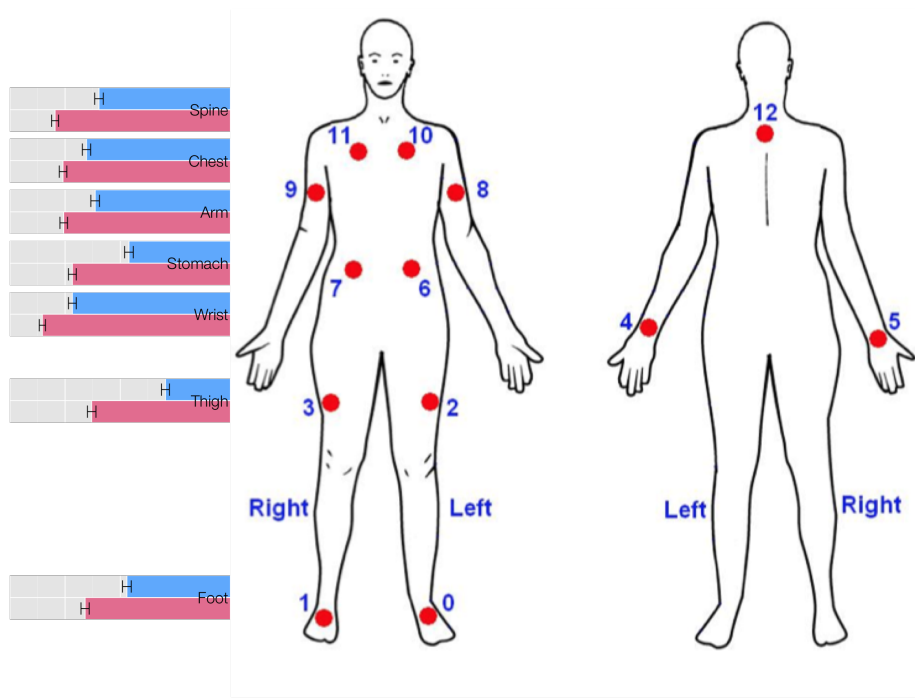


**Figure 3.7:** Mean Reaction Time of high intensity stimuli per body location and condition in Experiment 1.

0.05).

### Subjective Results

Users preferred wrists and arms the most, feet and thighs the least. When we asked which site they would choose for notifications, directional guidance, and for cues during exercise, they chose wrists, arms, and spine.



**Figure 3.8:** Detection Rate (DR) per body location on the body map; pink bars show DR during sitting conditions and blue bars show DR during walking conditions.

**Table 3.2:** Generalized Linear Mixed Model (GLMM) of Detection Rate (DR) in Experiment 1. *Pr* smaller than 0.05 indicates that DR is significantly different from the reference for that factor (e.g., from feet, for body sites). ‘\*’ indicates statistical significance.

	<i>coef</i>	<i>se(coef)</i>	<i>z</i>	<i>Pr(&gt;  z )</i>	O.R.
(Intercept)*	-4.02	0.31	-12.81	<0.001	0.02
Female	-0.40	0.25	-1.60	0.11	0.67
Wrists*	2.57	0.36	7.07	<0.001	13.11
Stomach*	1.28	0.36	3.54	<0.001	3.60
Thighs	-0.36	0.41	-0.89	0.37	0.69
Chest*	1.07	0.38	2.82	<0.001	2.90
Arms*	1.62	0.36	4.49	<0.001	5.06
Spine*	2.28	0.35	6.43	<0.001	9.73
Intensity*	2.02	0.11	18.73	<0.001	7.55
Walking*	-1.95	0.20	-9.56	<0.001	0.14
Workload	-0.06	0.07	-0.85	0.40	0.95
TrialID*	0.00	0.00	-2.82	<0.001	1.00
Female:Wrists	0.23	0.25	0.91	0.36	1.26
Female:Stomach	0.18	0.25	0.75	0.46	1.20
Female:Thighs*	0.62	0.25	2.47	0.01	1.87
Female:Chest	0.37	0.25	1.47	0.14	1.45
Female:Arms	0.11	0.25	0.43	0.67	1.11
Female:Spine	-0.21	0.25	-0.82	0.41	0.81
Wrists:Walking*	0.58	0.28	2.07	0.04	1.78
Stomach:Walking	-0.26	0.28	-0.93	0.35	0.77
Thighs:Walking*	-1.33	0.31	-4.25	<0.001	0.26
Chest:Walking*	0.86	0.28	3.14	<0.001	2.37
Arms:Walking*	0.66	0.27	2.42	0.02	1.93
Spine:Walking	0.16	0.28	0.59	0.56	1.18
Wrists:Intensity*	-0.35	0.15	-2.30	0.02	0.70
Stomach:Intensity*	-0.38	0.14	-2.72	0.01	0.69
Thighs:Intensity	-0.11	0.15	-0.72	0.47	0.90
Chest:Intensity	-0.10	0.15	-0.68	0.50	0.90
Arms:Intensity*	-0.35	0.14	-2.42	0.02	0.71
Spine:Intensity*	-0.41	0.14	-2.86	<0.001	0.67

**Table 3.3:** Results of Kruskal-Wallis tests on Reaction Time (RT), Experiment 1. “\*” indicates statistical significance.

Full Set

	chi-squared	df	p-value
BodySite*	434.3	12	<0.001
Task*	24.1	1	<0.001
Movement*	422.7	1	<0.001
Gender	11.3	1	0.596
Intensity*	4517.2	4	<0.001
TrialID	509.4	559	0.162

Subset: High Intensity

	chi-square	df	p-value
BodySite*	130.9	12	<0.001
Task*	48.4	1	<0.001
Movement*	62.6	1	<0.001
Gender	1.3	1	0.249
TrialID	487	528	0.899

Subset: All Detected

	chi-square	df	p-value
Intensity*	4517	4	<0.001

## 3.5 Experiment 2: Random vs Expected Site

In Experiment 1, participants did not know which of the 13 sites would receive the next vibration, whereas in actual wearable use, usually only one site would be used. We theorized that there could be a performance cost associated with scanning multiple body sites, and therefore performed a second experiment (Experiment 2) where site expectation mode is controlled. To maintain experiment size, we also removed the two least-likely body site pairs (stomach and chest), and the visual task condition because it did not have a significant effect on DR, our primary metric. All other aspects were identical to Experiment 1. In addition to verifying H1-H3 and H5 from Experiment 1, we examined the following Experiment 2 hypotheses:

**H6** Expectation of site increases DR and decreases RT.

**H7** Expectation reduces the effect of movement.

**H8** Expectation impacts different genders differently.

### 3.5.1 Design

In Experiment 2, we used five paired body sites (Table 3.1). Half the male and half the female participants first sat in a chair and subsequently walked on a treadmill, while the other half walked on a treadmill first then sat in a chair. During half of the walking and half of the sitting trials, the vibrations were displayed in 10-trial clusters (5 intensities  $\times$  2 repetitions) at each body site and participants were informed of the site (Expectation condition). During the other half, the vibrations were randomly displayed on any site and participants were not informed of location.

After signing consent forms, participants completed the following training steps (1-3 are the same in Experiment 1):

#### *Training 1:*

1. Experience maximal vibration on each site.
2. Experience each of the five intensities on the wrist.
3. Respond to ten maximal vibrations at random sites.



**Training 2:** Respond to 4 counterbalanced conditions of:

4. Sitting+Expectation: sets of four vibrations, random intensity on three randomly selected sites, sitting.
5. Sitting+No Expectation: twelve vibrations of random intensity on randomly selected sites, sitting.
6. Walking+Expectation: sets of four vibrations, random intensity, on three randomly selected sites, walking.
7. Walking+No Expectation: twelve vibrations of random intensity on randomly selected sites, walking.

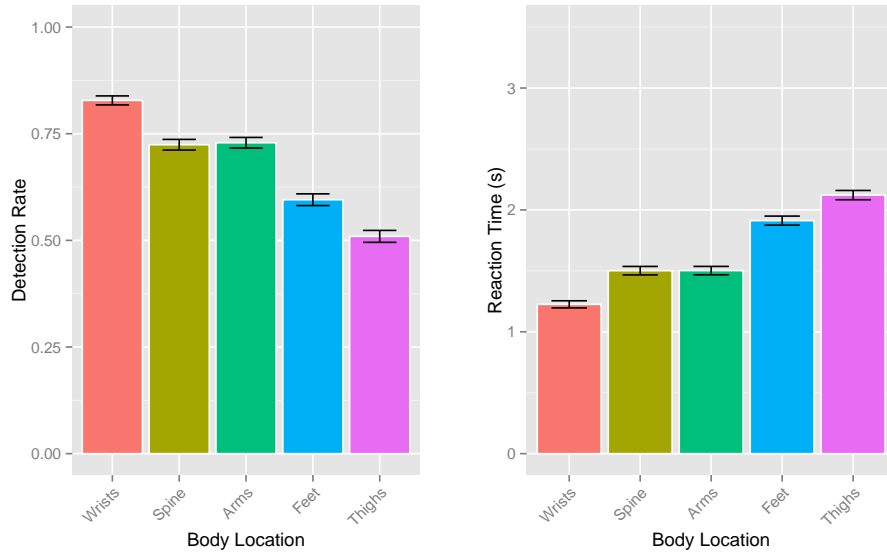
**Experiment:** Respond to 100 vibrations (location  $\times$  intensity  $\times$  repetitions) in four conditions, order counterbalanced by participant. Participants took a short break after training and between the second and third conditions, and filled questionnaires at the beginning (profile) and end (preferences) of the experiment. Each person was compensated \$15 for participation. Total experiment time was 90 minutes.

### 3.5.2 Results

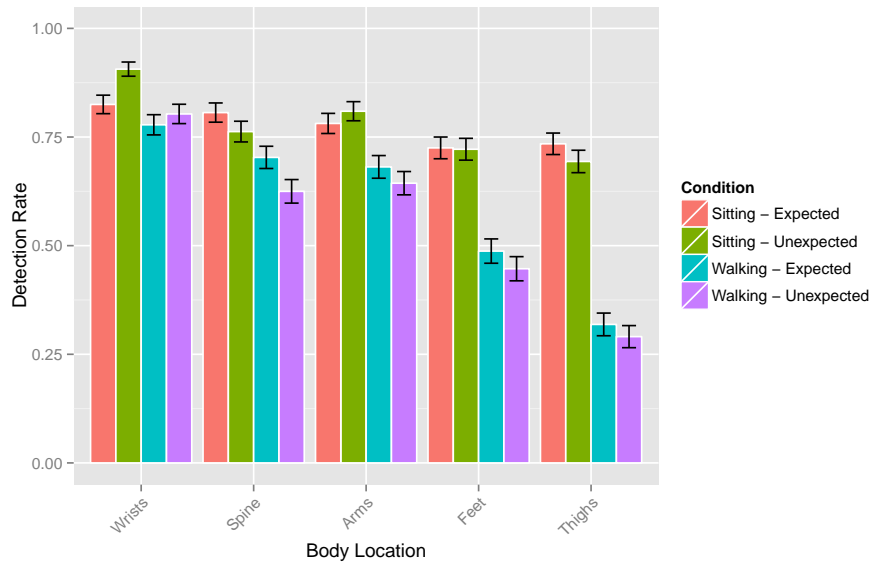
For this experiment, 16 participants (8 male) volunteered; none were from Experiment 1. These were distributed in age as 22-24 ( $n = 4$ ), 25-27 ( $n = 6$ ), 28-30 ( $n = 6$ ); in height as tall ( $n = 4$ ), average ( $n = 10$ ), short ( $n = 2$ ); and body type as ecto ( $n = 5$ ), meso ( $n = 9$ ), endomorph ( $n = 2$ ). In prior year, participant use of portable devices with tactile feedback was distributed as daily ( $n = 9$ ), 2-3 times/week ( $n = 2$ ), 1 times/week ( $n = 1$ ), <1 time/month ( $n = 4$ ); and participants used a treadmill <1 time/year ( $n = 3$ ),  $\leq 1$  times/month ( $n = 9$ ), 2-3 times/month ( $n = 1$ ), 1 time/week ( $n = 3$ ). 4/16 reported themselves lefthanded. As in Experiment 1, false positive effect was negligible (0.8%).

#### **Detected/Missed Stimuli DR**

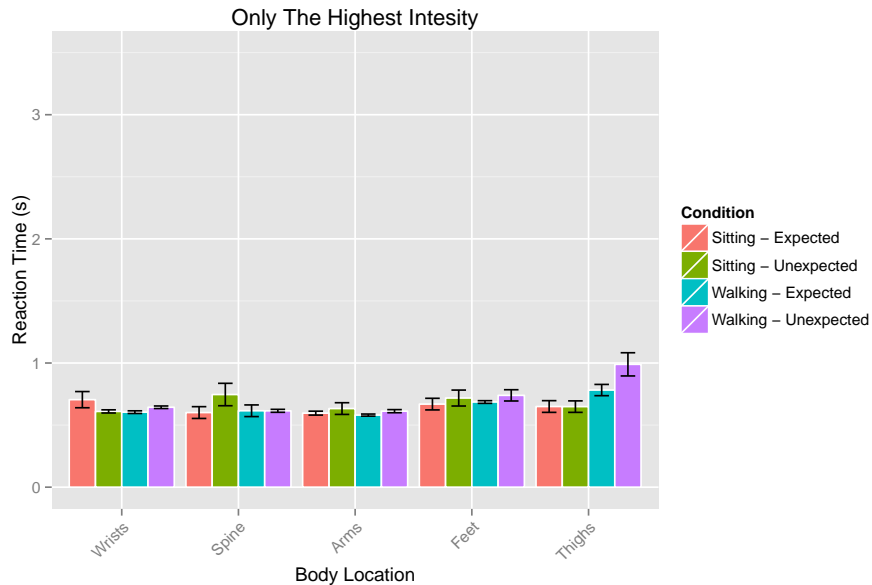
Our GLMM analysis was conducted as for Experiment 1. With expectation is the reference for the new expectation factor. Main effects: All body sites are significantly different from feet (Table 3.4, Figure 3.9), with wrists and spine best and



**Figure 3.9:** Mean Detection Rate (left) and Reaction Time (right) per body location in Experiment 2.



**Figure 3.10:** Mean Detection Rate per body location and condition in Experiment 2.



**Figure 3.11:** Mean Reaction Time of high intensity stimuli per body location and condition in Experiment 2.

feet worst at detecting vibrations. Walking greatly decreases detection odds. As expected, intensity is significant. Gender has a significant effect on the odds of detecting a vibration (females seem to have higher DR) but it is cancelled out with the interaction effects (see below). TrialID (time into the experiment) and Expectation have no significant effect on the odds of detecting a vibration. An interaction between Intensity and spine reduces the main effect of Intensity, suggesting Intensity plays a less important role for spine than for other body sites. Movement decreases detection odds at all sites (Figure 3.10); wrists and spine least, thighs and feet most. Again, positive interaction coefficients for Movement and sites do not compensate for the negative main Movement coefficient. Movement:Intensity reduces the main effect for Movement. The interaction effect between Gender and body sites indicates that females have higher odds of detection only on their feet.

### Reaction Time (RT)

As with Experiment 1, we ran two sets of Kruskal-Wallis tests: one on the entire data set, using 3500 ms for missed vibrations, and another on the subset of high-

intensity trials where most of the vibrations (98.4%) were detected (Table 3.5). Both tests show that Intensity, Movement, Expectation and Gender have a significant effect on RT but Trial ID does not (Figure 3.11). More intense vibrations are detected faster, movement and lack of expectation increase RT, and males are slightly faster to respond than females. A Kruskal-Wallis test on Intensity for the trials where vibrations were detected showed a significant effect of Intensity on RT (Table 3.5, Subset=All detected).

### **Subjective Results**

Experiment 2 participants preferred spine and wrists the most, feet and thighs the least (relative to Experiment 1, spine replaced arms as a preferred site). For notifications and directional guidance they chose wrists and for exercise cues they chose spine.

## **3.6 Summary and Discussion**

We begin our discussion with an examination of our hypotheses, then further reflect on their implications.

**H1 - Vibration Intensity:** Both Experiment 1 and Experiment 2 showed that increasing vibration intensity strongly increases detection odds and reduces reaction time, supporting H1. However, impact of DR varies across the body. In Experiment 1, DR increases with intensity for all body sites but less so for spine, wrists, arms and stomach; in Experiment 2, less so for the spine.

**H2 - Body Sites:** Experiment 1 and Experiment 2 consistently show that wrists and spine are most sensitive in detecting vibrotactile signals, whereas feet and thighs are least sensitive. As described for H1, body sites are differentially sensitive to intensity in terms of absolute detection. However, Experiment 1 and Experiment 2 also demonstrate that response time for high intensity signals ( $\geq 98\%$  detection) is similar across the body. Thus, H2 is confirmed for detection rate, but not for response time.

**H3 - Movement:** Walking significantly reduces odds of detecting a vibration, and increases reaction time even to high intensity vibrations. Both experiments further confirmed that the DR of thighs and feet are most affected by walking. H3 is thus

**Table 3.4:** GLMM of DR in Experiment 2. *Pr* smaller than 0.05 indicates that DR is significantly different from the reference for that factor. coef greater than zero indicates increased odds of detecting a vibration. ‘\*’ indicates statistical significance.

	coef	se(coef)	z	<i>Pr</i> (>  z )	O.R.
(Intercept)*	-1.36	0.35	-3.85	<0.001	0.26
Female*	0.89	0.34	2.63	0.009	2.42
Thighs*	0.65	0.28	2.32	0.021	1.92
Wrists*	1.84	0.29	6.29	<0.001	5.32
Arms*	0.76	0.29	2.61	0.009	2.14
Spine*	1.84	0.28	6.66	<0.001	6.28
Intensity*	1.70	0.11	15.72	<0.001	5.50
Walking*	-2.91	0.25	-11.48	<0.001	0.05
Randomized	-3.01	0.19	-0.05	0.960	0.99
TrialID	0.00	0.00	-1.78	0.075	1.00
Female:Thighs*	-1.02	0.25	-4.14	<0.001	0.36
Female:Wrists*	-1.39	0.26	-5.26	<0.001	0.25
Female:Arms*	-0.62	0.26	-2.40	0.016	0.54
Female:Spine*	-1.45	0.25	-5.91	<0.001	0.23
Female:Randomized*	-0.42	0.16	-2.63	0.009	0.65
Thighs:Intensity	-0.17	0.14	-1.27	0.204	0.84
Wrists:Intensity	-0.08	0.16	-0.47	0.638	0.93
Arms:Intensity	0.24	0.16	1.51	0.132	1.27
Spine:Intensity*	-3.39	0.13	-3.00	0.003	0.68
Thighs:Walking*	-1.26	0.32	-3.99	<0.001	0.28
Wrists:Walking*	1.84	0.30	6.20	<0.001	6.30
Arms:Walking*	1.16	0.29	3.96	<0.001	3.18
Spine:Walking*	1.54	0.27	5.70	<0.001	4.68
Thighs:Randomized*	-0.09	0.24	-0.38	<0.001	0.91
Wrists:Randomized*	0.87	0.26	3.31	0.001	2.38
Arms:Randomized	0.16	0.26	0.63	0.531	1.17
Spine:Randomized	-0.31	0.24	-1.27	0.204	0.73
Intensity:Walking*	0.28	0.09	3.17	0.002	1.33

**Table 3.5:** Results of Kruskal-Wallis tests on RT, Experiment 2. ‘\*\*’ indicates statistical significance.

Full Set

	chi-squared	df	p-value
BodySite*	284.450	8	<0.001
Randomization*	10.320	1	0.001
Movement*	402.495	1	<0.001
Gender*	31.916	1	<0.001
Intensity*	3116.700	4	<0.001
TrialID	358.017	399	0.931

Subset: High Intensity

	chi-squared	df	p-value
BodySite*	149.65	8	<0.001
Randomization*	9.3279	1	0.002
Movement*	72.8988	1	<0.001
Gender*	36.237	1	<0.001
TrialID	380.7202	384	0.538

Subset: All detected

	chi-squared	df	p-value
Intensity*	3116.7	4	<0.001

confirmed.

We note that while thighs and feet moved the most during walking in this experiment, participants also swung their arms. Walking was chosen as a representative movement in mobile contexts. Further work is required to establish more generalizable patterns of body sensitivity to different types of movement; but the present result is highly relevant to designing for mobile uses.

**H4 - Visual Workload:** Our visual workload task did not have any apparent effect on vibration detection. It did significantly impair reaction time, increasing even for the most intense vibrations. H4 is thus partially rejected and partially confirmed. There is no evidence in our results of body site specificity in impact of the workload task.

Wickens proposes four qualities to describe workload: mental stage, modality,

channel and processing code [171]. Stage can be perceptual or responsive. Modality is typically visual or auditory, and it is better to spread work across modalities rather than on time-sharing a single modality. Visual workload can be focal or ambient without competition. Codes are analogue/spatial or categorical/symbolic. Typically, people perform simultaneous manual and focal tasks well. Thus, our visual task (focal) and vibration response modality (manual) do not compete heavily for the same resources.

Ferris et al. presented vibration patterns from back-mounted tactors to participants in a driving simulation, with categorical (TC) or spatial (TS) visual tasks [38]. Their visual task had a significant effect on RT but similarly to our results, the overall effect of task on accuracy (detection of the type of visual stimuli) did not reach significance; in particular, while their TC task impacted accuracy, their TS task (which seems more similar to our visual task) did not.

We did not choose a harder visual task or one which more specifically interfered with detecting and responding to signals because we aimed to simulate a typical mobile context, *i.e.*, watching for other pedestrians and cars over a wide field of view. However, there will be situations when more severe competition does occur, even if not endemic.

***H6 and H7 - Expectation:*** Expectation had a significant effect on detection only at the wrists where, surprisingly, it reduced detection odds. One possible explanation is that in the no-expectation mode where in recent trials a perceptually weaker stimulus had been felt elsewhere, the wrist percept was relatively more salient. Another possibility is that sensory adaptation acted as a side effect of sending a number of signals to the wrists. Because wrists detect more vibrations than other sites, the adaptation effect on wrists should be larger than elsewhere. However, the positive effect of expectation (which cancels adaptation on other body sites) is not large enough for wrists to compensate for adaptation. Finally, there is a one in 20 chance that this result is simply due to chance; our analysis employed a 95% confidence level.

Expectation significantly reduced response time: scanning the whole body when the stimulus site is unknown slows the process of vibration detection and response. Thus, H6 is confirmed with respect to reaction time. Expectation did

not have a significant effect on detection rate and (compared to movement) it had a very small effect on reaction time. Therefore, expectation alone cannot cancel the effect of movement, and H7 was not confirmed.

**H5 - Gender:** In Experiment 1, males were better than females at detecting vibrations on the chest and stomach, the sites omitted from Experiment 2. For the remaining sites, males always detected vibrations on wrists and spine better than females. However, Experiment 1 and Experiment 2 disagree as to the body sites where females were best: thighs in Experiment 1, arms and feet in Experiment 2.

In general, females' reaction times were slightly longer than males, with the exception of the feet, where females were faster. Thus overall, while H5 is confirmed (gender does have some impact) the difference is not consistent or large.

### **Subjective Results**

On average, Experiment 1 participants preferred vibrations on their wrists most, arms the second; Experiment 2 participants preferred spine, then wrist. Grouping the 32 participants of both experiments, there is a tie for highest preference between spine and wrists. Both groups disliked vibrations on their feet by far the most; thigh is second least preferred.

Both groups chose wrists for notification applications, arms and wrists for directional guidance, and spine as the most appropriate spot for vibrotactile signals during exercise.

## **3.7 Conclusion and Future Work**

We ran two experiments to study the differences between sensitivity of several body sites to vibrotactile signals. We narrowed down the number of body sites to those most practicable for wearable haptics and mobile applications: wrists, upper arms, outer thighs, feet, chest, stomach, and spine. Most of these locations have been suggested or used in past wearable tactile systems such as belts, back arrays, wrist and arm bands, tactile shoes, and most commonly, cellphones in pockets (on the thighs).

We compared these body sites under conditions of presence or absence of a visual workload, sitting in a chair or walking on a treadmill, and with or without



knowledge of location of the next stimuli. We also looked at gender differences, and considered five vibration intensities.

One of our most important and perhaps surprising results is that expectation of stimulus location does not improve detection rate, under the conditions of Experiment 2; but it does decrease reaction time. We did not include a visual workload condition in Experiment 2 because of its limited impact in Experiment 1; however, it will be of interest to see if expectation can counteract negative effects of workload tasks which cause more interference.

The fact that our workload task did not interfere with vibration detection in Experiment 1, *i.e.*, even when the next vibration location was unknown and participants had to scan their body to detect it, is an encouraging result. To the extent that this kind of workload is realistic, vibrotactile signals can still “get through” anywhere on the body even under load conditions, albeit more slowly when the user is under mental effort. The implication is that the detection and some kinds of workload typical of mobile contexts do not directly compete for mental resources.

In another notable result, the thigh was among the least effective and least preferred stimulus site we tested; and yet, the front pocket is a common location to stow a mobile device, particularly for men.

Although H1-H5 seem to be predictable from past work, none of our hypotheses have ever been confirmed in a controlled comparison with realistic display technology and is very necessary from a design perspective. For example, H1 confirmation informed/justified our choice of intensity levels and assumptions on its linearity (which were used later in the GLMM). Furthermore, the secondary results of H2-H5 (*e.g.*, interaction effects, change in the ordering pattern) were not predictable from published data.

### **3.7.1 Design Guidelines**

From our results, we propose the following guidelines. We note that these heuristics have particular relevance for applications which have either of two attributes: intolerance to missed signals, and/or a requirement for fast responses. The first is typified by tasks that rely on background processes, such as notification, or those where signals carry notable content, *e.g.*, haptic icons [100] where inattention could

distort the signal's meaning. The second includes gaming and time-and-safety-critical guidance systems. Others have need of both, *e.g.*, driving systems that use both guidance and notifications.

***Location, Location, Location*** Wrists and spine are generally best for detecting vibrations, and are also the most preferred, with arms next in line. Feet and thighs are poor candidates for vibrotactile displays, exhibiting the worst detection performance of those we tested and ranking lowest in user esteem. However, for reaction time, location does not matter.

***Stronger Vibes Are Felt Faster*** Unsurprisingly, increasing intensity increases detection rate and reduces reaction time, particularly on the lower-body sites tested here. This result does not imply that strong vibrations will always be preferred or appropriate; but when a notification must get through, intensity increases salience.

***Don't Take Movement For Granted*** Movement can decrease detection rate and increases response time. Walking (the movement we tested) affects lower body sites the most. For applications that involve a considerable movement, other factors such as intensity and body location need to be adjusted to compensate for this.

***Visual Workload Slows Users Down*** Although workload of the type we employed (visual search) does not apparently impact vibration detection rate, it does increase response time. Therefore, expect some lags and irregularities in user response to vibrotactile displays in visually demanding situations.

***Users React Slower to Unexpected Vibrations*** Multiple site tactile interfaces mean surprises for the user; single site interfaces mean the user always knows where to “watch”. If reaction time is critical, designers should be cautious in proliferating display sites across the body. If only detection matters and time is not critical, the number of sites does not matter, and the redundancy may in fact prove more robust to local interference.

***Gender Differences do not Change Our Suggestions*** Men detect vibrations on their wrists and spine a little better than women. Women detect vibrations somewhat better on thighs and arms. However, wrists and spine are still the best choices for both genders, and differences are not large.

### **3.7.2 Future Work**

We embarked on this study because we required guidelines of this sort to reduce design errors and shorten the iterative design process for our wearable haptic systems. These results solve our immediate needs, and the body sites investigated are a good sample of those that might ever be successfully used in wearable contexts.

However, other factors deserve broader investigation. Of greatest importance will be to encompass a broader set of workload tasks and movement types beyond visual search and walking, and to incorporate auditory and vibrotactile noise of typical environments such as moving vehicles.

## **3.8 Acknowledgment**

This work was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC). User data were collected under University of British Columbia's Research Ethics Board approval H01-80470.

## Chapter 4

# Cadence Measurement

*Everywhere is walking distance if you have the time.*  
— Steven Wright

We<sup>1</sup> present an algorithm that analyzes walking cadence (momentary step frequency) via frequency-domain analysis of accelerometer signals available in common smartphones; and report its accuracy relative to published state-of-the-art algorithms based on data gathered in a controlled user study. We show that our algorithm, Robust Realtime Algorithm for Cadence Estimation (RRACE), is more accurate in all conditions, and is also robust to speed change and largely insensitive to orientation, location on person, and user differences.

RRACE’s performance is suitable for interactive mobile applications: it runs in realtime ( $\sim 2$  s latency), requires no tuning or *a priori* information, uses an extensible architecture, and can be optimized for the intended application. In addition, we provide an implementation that can be easily deployed on common smartphone platforms. Power consumption is measured and compared to that of current commercially available mobile apps.

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This chapter appears with minimal modifications in [79]:

- I. Karuei, O. S. Schneider, B. Stern, M. Chuang, and K. E. MacLean. RRACE: Robust Realtime Algorithm for Cadence Estimation. *Pervasive and Mobile Computing*, (0):52–66, 2014. ISSN 1574-1192

<sup>1</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.

We also describe a novel experiment design and analysis for verification of RRACE’s performance under different conditions, executed outdoors to capture normal walking. The resulting extensive dataset allows direct comparison (conditions fully matched) of RRACE variants with a published time-based algorithm.

We have made this verification design and dataset publicly available, so it can be re-used for gait (general attributes of walking movement) and cadence measurement studies or gait and cadence algorithm verification.

## 4.1 Introduction

Contemporary smartphones carry a wealth of sensors which can be used to estimate aspects of a user’s context and activities that are of value in a multitude of applications. One notable example, walking cadence (“the beat, time, or measure of rhythmical motion or activity” – Merriam-Webster; used hereafter to refer to step frequency as estimated in realtime), has broad utility for applications that support fitness, rehabilitation, gaming, navigation, and context awareness. But available cadence detection methods require unrealistically specific placement and sensor calibration to achieve viable performance. There is a need for realtime cadence detection that is robust to carrying method.

Current realtime mobile cadence detection methods are largely based in the time domain, detecting timing of individual footfalls which themselves are estimated when an accelerometer signal exceeds a threshold. This threshold dependency is not ideal from a usability standpoint because the threshold is specific to many parameters – for example, Melanson et al. show that threshold-based pedometer accuracy changes dramatically by age, weight, and height [106]. Detection accuracy consequently necessitates device (or additional sensor) placement in a location known to the algorithm, on one of a small number of body sites with highly regular movement – *e.g.*, the pocket, on the hip, or the leg [43] – at a specific orientation, and with user-specific calibration to adjust for weight, height, and body shape of the user. This invokes a harsh tradeoff between reliability and usability [47].

Frequency methods for cadence detection have received little attention to date, yet in contrast to acceleration thresholds, there is substantial qualitative common-

ality in frequency profiles as a function of position in various body locations [93]. Because the frequency and wavelength of the acceleration depend on the time interval between footfalls and the wave's shape and amplitude depend on the individual and location on the body, theoretically the major frequency component of the acceleration should be more robust to the individual-, location- and model-specific amplitude concerns which make time-based thresholds so problematic.

In this chapter, we describe an algorithm, Robust Realtime Algorithm for Cadence Estimation (RRACE), to analyze cadence through a frequency-domain analysis of movement, and report its accuracy based on data gathered in a user study. RRACE's basic structure is a computationally efficient moving window that is subjected to a spectral analysis followed by an analysis of frequency peaks. Empirically, we found that performance peaks at a window length of 4 s, producing about 2 s latency including computational delay. This algorithm is extendable, allowing for improvements with advanced filtering or harmonic analysis, and can be used to provide spectral information for classification of gait (general attributes of walking movement) and other gait analysis applications.

While others have reported using frequency-based approaches [93, 178], our approach's exceptional robustness is due in part to its ability to utilize non-uniformly sampled data (the most readily available) and in part to the reliance on acceleration vector magnitude (the component unaffected by orientation) to determine cadence without knowledge of the placement of the device on the user's body.

Our contributions are (a) a cadence detection algorithm that can work across many body locations, is robust to change of orientation, and does not require calibration; (b) an experimental setup for assessing the accuracy of a gait detection method across many body locations, outdoors and under normal, unconstrained walking conditions; (c) performance data examining the effects of body location and speed on the algorithms we tested; (d) a thorough comparison between our frequency-based gait detection method and the highest-performing published time-based acceleration threshold method, hereafter referred to as the time-based method; and (e) an implementation that can be easily deployed on common smartphone platforms.

After discussing related work, we describe the RRACE algorithm and present our pilot and main validation experiment with RRACE running in realtime on a

smartphone. We then compare RRACE to the time-based method, and conclude with a discussion of our findings and plans for future work.

## **4.2 Related Work**

To ground the presentation of our algorithm and evaluation, we first discuss real-time gait and cadence detection and its applications, then examine the state-of-the-art in time-domain and frequency-domain methods of cadence detection.

### **4.2.1 What is Realtime Cadence Detection Good For?**

Gait and cadence information is relevant to many current and future mobile applications. Often attributed to Thomas Jefferson [172], the modern pedometer has long been a fitness tool for dedicated walkers and runners. Today's ever-expanding lineup of smartphone app versions further support logging, mapping, calorie burning estimates and social media [46, 115, 164].

Kavanagh and Menz point out the popularity of accelerometer-based systems for human gait measurement and give a broad overview of accelerometer-based gait measurement systems with suggestions on optimal use conditions, reliability, and applications [80].

A number of fitness applications and products focus on automaticity, personalization, and direct feedback to increase motivation. As early as 2008, UbiFit used persuasive technology in its visual displays (using a metaphor of a garden's healthiness) of activity and goal achievement [25]. The Nike+iPod Nano, developed by Nike Inc. (Beaverton, OR, USA), measures distance, speed, and energy expenditure and can be programmed to play a motivational song when necessary [113]. Endomondo app, developed by Endomondo (Copenhagen, Denmark), claimed to be the most highly-reviewed activity monitoring Android app, uses a GPS signal to track speed, distance, duration, and calories burnt for running, cycling, and other sports [33]. Runtastic Pedometer by Runtastic GmbH (Linz, Austria), another Android app, also uses accelerometer data to count steps and measure calories burnt [137].

MPTrain (later extended to be TripleBeat) goes further by selecting and playing music with specific features to support pace goals like speeding up and slowing

[31, 115]. Garmin (Olathe, KS, USA) produces the Forerunner 910XT, a multi-sport watch that can be used for running, biking, and swimming [49]. It can detect walking steps and swimming and cycling strokes using its 3-axis accelerometers, measure elevation by a barometric altimeter, and be paired with a heart rate monitor; as for many tools, users can plan their workouts and analyze their activity through a number of metrics. The burgeoning area of exercise games could benefit from realtime knowledge as well; previous work has linked game performance to step count [95] and overall physical activity [48].

All-day wearable activity monitoring currently includes successful commercial products like the Nike+ Fuelband [112], developed by Nike Inc. (Beaverton, OR, USA), and the FitBit, by FitBit Inc. (San Francisco, CA, USA), [41] and mobile apps such as Endomondo [33] and Runtastic Pedometer [137]. These products, using 3-axis accelerometers along with various extras like GPS and ambient light sensors, aim to track and support goal achievement including steps taken, calories burned, and hours of sleep, providing a global view of activity levels as distributed over the day, week, and longer periods of time. Based on our informal measurements, Fuelband (worn on the wrist) appears to be less precise in measuring steps, while we saw Fitbit's error remain within a 5% bound and Runtastic Pedometer's within a 10% bound when counting steps.

These devices are representative of the current market selection, which is rapidly moving. Popularity and supported price points (presently \$100-200 USD) highlights growing consumer interest in holistic, conveniently acquired perspectives on their activity.

Meanwhile, it is possible to fuse cadence estimates with other data to identify more complex user states. When Global Positioning System (GPS) is unavailable, they can augment navigation algorithms through dead-reckoning [105, 178]. Accurate cadence information provides a valuable feature for mobile fitness games and detailed guidance tasks that require higher-resolution data (*e.g.*, skipping, hopping, "turn here") in addition to GPS and biometrics [47]. Context-aware applications benefit from discerning walking, running, or sedentary states by using gait along with posture, auditory and other data to optimize notification timing [69, 81, 82]. Cadence can also supplement interior GPS and localization systems [1]. In all of these examples, accuracy and convenience of mobile collection is paramount.



A number of specialized, commercially available devices record and analyze human movement with good accuracy for medical purposes such as clinical, biomechanical, physical therapy, and movement disorders research, as well as athletic tuning. *Movement Monitors* by APDM Movement Monitoring Solutions (Portland, OR, USA) are watch-sized Inertial Measuring Units (IMU), intended to be worn on multiple sites simultaneously (wrist, ankle, belt, and sternum straps), using accelerometers, gyroscopes, and magnetometers [4]. Industrially, IMUs are a valuable diagnostic and research tool for industrial vibration or movement monitoring, inertial guidance, virtual reality, or any application where precise monitoring of subtle movement is required. However, in these specialized situations it is feasible to wear or install a potentially expensive specialized device, precisely calibrated and location constrained. This is not the case for most potential consumer uses of cadence or gait detection.

#### 4.2.2 Sensor Type

Traditional pedometers identify individual steps using mechanical or piezoelectric sensors. Purely mechanical sensors detect a step if acceleration surpasses a threshold, measured when a sensor element strikes a surface. Piezoelectric sensors vary in form and sophistication. Like their mechanical cousins, many operate on an acceleration-threshold principle while more sophisticated devices compare an acceleration time series to a model of a step. The variants found in contemporary smartphones and IMUs, however, typically rely on 3D accelerometers. Their output can be processed in the same way as a piezoelectric or mechanical sensor, but also give rise to new algorithmic possibilities as described below.

There has been some sensor-based improvement in pedometer accuracy observed for piezoelectric relative to mechanical sensors, in particular at very slow walking speeds, likely due to increased sensitivity. A 2004 treadmill-based analysis of mechanical and piezoelectric pedometers found error reduced with speed for slow walking: 29% ( $< 0.89$  m/s), 9–26% (0.89 to 1.34 m/s), and 4% ( $> 1.34$  m/s)<sup>2</sup> for mechanical pedometers. In a second variant, at speeds between 0.80 and 0.89 m/s, the piezoelectric's error was  $< 3\%$  as compared to the mechanical sensors's

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<sup>2</sup>1 m/s = 2.24 mph

5 – 48% [106]. The lowest error reported (0.3%) is for a piezoelectric sensor worn on the ankle [43]. In these studies, all pedometers were tested while worn on their optimal and calibrated specified location with specific orientation.

Accelerometer-based instruments are sampled using an embedded CPU, and accessed by an application through its operating system. Thus, their usable accuracy is both due to the sensor itself, and the quality, rate and latency of access to its output permitted by the operating system; these parameters all vary widely and their relative impact is not generally discussed. Current overall performance levels are discussed below.

### **4.2.3 Estimating Cadence**

#### **Time Domain**

Whether standalone or in an iPhone app, an algorithmic (programmed) cadence estimate derived in the time domain is based on thresholds or peaks and step model parameters. These are in turn generated from user-supplied information such as body mass and height, as well as the sensor's known or constrained Location on Person (LOP), and details of the hardware platform. Without this, accuracy is poor (as we will demonstrate in Section 4.5.2), and this need for substantial context and/or limitations in where and how they can be worn is their major drawback.

The most straightforward solution for cadence estimation of any type is to analyze acceleration in the time domain and detect individual footfalls. This requires just a single axis of acceleration, and produces algorithms that are computationally lean. Time domain approaches can be quite effective when context information is known or constrained, being simple and reasonably accurate. A brief frequency-based peak-detection algorithm (such as the one we compare later in this chapter) delivers a latency equivalent to the last two steps.

Yang et al. sampled a waist-mounted tri-axial accelerometer module with built-in low pass filter, and computed autocorrelation in the time domain to measure cadence in realtime [174]. They reported a mean absolute percentage error of 4.89% when comparing their results with cadence measurements from the synchronized video. Their algorithm used a 3.5 s window.

The specifics of most commercial pedometer algorithms such as Runtastic Pedometer [137] are unavailable. However, an MPTrain publication [115] identifies its step detection as an adaptive accelerometer threshold with a low-pass filter, and report its accuracy as comparable to standard piezoelectric pedometers [115]. We further describe the MPTrain algorithm in Section 4.5.1, as we use it for comparison with our algorithm.

### **Frequency Domain**

Frequency analysis has been instrumental in revealing interesting characteristics of gait (*e.g.*, discriminating the steps of the left and right foot [181] or comparing acceleration frequency content of two devices to determine if they are carried by the same person [93]). Zhao et al. use gait detection in assisted GPS systems [178], and identify the uncertainty of the sensor location as an important issue. Their solution is to classify sensor location by extracting time and frequency domain features, then choosing a dead-reckoning algorithm according to the classification result.

Unlike cadence estimation in the time domain, where each footfall is recorded and time-stamped, a frequency-based algorithm looks at a bigger picture: it identifies the signal's major frequency components during a given window of time. At the cost of not detecting single footfalls and (typically) a larger delay to collect multiple samples, a frequency-based algorithm is far less dependent on signal shape and amplitude. This is because a frequency-based algorithm can distinguish between the major frequency component of the signal influenced by the repetition intervals (*i.e.*, step duration), and the harmonics influenced by placement of the sensor and the subject's unique walking pattern and noise. A frequency-based cadence estimation algorithm is thereby *theoretically* more robust to individual differences and sensor location than a time-based approach.

Thus, in applications where the exact time of footfalls is not required but ease and flexibility of use is valued, a frequency-based algorithm seems a promising approach, and is the one we took here. For related reasons, autocorrelation is another avenue that deserves attention, although it is beyond the scope of this chapter. For either, achievable latency and accuracy then become the crucial issues, and

necessitated a development plan that included careful validation. Of published algorithms, the frequency-based ones state that they depend on proprietary info such as placement on the body or adjustments to the parameters to compensate for user differences. Kavanagh and Menz note the necessity of user-specific calibration procedures and errors caused by change of orientation [80]; they present an elaborate list of accelerometer attachment methods from past research with every one of them using a single location for the placement of the sensors. Zijlstra and Hof for example, like the majority of other researchers, placed accelerometers on the lower trunk [181]; specifically, they fixed the position of accelerometers at the dorsal side of the trunk with a fixed orientation. To our knowledge no realtime frequency-based methods have been reported for measuring cadence that uses the built-in sensors of a commodity smartphone and works out-of-the-box (*i.e.*, without calibration).

#### **4.2.4 Performance Assessment of Cadence Estimation Algorithms**

Published performance data are a rarity in cadence and gait estimation. Schneider et al. elaborate on the challenge of comparing performance of such algorithms for realtime gait classification and accelerometer-based activity recognition [143], which are partly due to the large number of possible parameters and settings, and format of testing. The sheer logistical effort of precise validation may be an even more significant problem: natural walking is best done outdoors, and the technique in question must be compared with one or ideally two additional, independent and highly accurate ‘gold standard’ methods that are sampled at the same time. As can be seen in the following pages, this entails a considerable commitment in setup and data collection that most published works have omitted.

Furthermore, many of the examples we have cited are proprietary algorithms in commercial products released within a fast-moving market, with minimal or zero information available about their function or performance. Without easy access to their internal realtime data streams (for example, FitBit must compute realtime step frequency, but does not share it with the consumer even post-hoc) it is difficult for a 3rd party to independently verify their accuracy and other parameters.

Much of this difficulty would disappear with the availability of standardized

datasets: published trajectories of carefully collected and documented acceleration data, ideally as streams obtained simultaneously from multiple points on the body during a range of walking conditions. Different algorithms can then easily be compared. This practice is common in other communities, such as machine learning, but there is no standard data set for gait detection that we know of. For this reason, we are making our own dataset available, as detailed in Section 4.4.

### **4.3 Approach: The RRACE Algorithm**

To support other research in our lab, we required a reliable, outdoor-ready cadence detection method that is both unconstrained in body location, and does not require users to acquire or wear specialized hardware.

Our goal was therefore to develop an algorithm that measures cadence at the same rate of accuracy as the best on record [35] (5% error) or better, that works on typical smartphones and is independent of orientation, placement on the body and individual wearer’s physiology, and works out-of-the-box and in realtime. We also predicted that due to their growing ubiquity, a highly usable, smartphone-ready cadence detection algorithm would enable many new possibilities beyond our immediate needs. We chose a frequency-based approach for the reasons cited above, and developed an implementation that solved a number of inherent complexities as described below.

#### **4.3.1 Overview**

Our cadence-detection algorithm, (RRACE), performs a spectral analysis on a four-second window of sampled 3-axis accelerometer data. Our approach has three characteristics that make it appropriate for realtime cadence estimation on mobile phones: (a) it is independent of body location and subject differences (as discussed before), (b) it is robust to orientation, and (c) it is robust to sampling irregularities.

Without published details or even the identity of other frequency-based algorithms, it is difficult to compare our approach to others on theoretical grounds. However, all the frequency based algorithms of which we are aware report using fixed-rate sampling (*e.g.*, [30]), and, as some of them point out, for smartphone signals this would likely be a source of considerably reduced accuracy.

### 4.3.2 Implementation Details

**Supporting orientation-invariant information:** To estimate overall movement from this measure, we use the magnitude (Euclidean or L-2 norm) of the three accelerometer axes  $(x, y, z)$  as our signal, as in [93]. This is a simple path to orientation invariance which we later show to be effective.

**Accommodating Non-uniform Sampling (FASPER):** Most smartphones supply accelerometer data which are not sampled at a constant rate (*e.g.*,  $25 \pm 5$  Hz); our data indicate that irregularities in accelerometer sample intervals are endemic. For example, the variance in the data analyzed for this chapter is:

- Sampling period: *mean* = 40.0 ms, *median* = 31.0 ms, *SD* = 37.7 ms
- Sampling frequency: *mean* = 127.7 Hz, *median* = 32.3 Hz, *SD* = 231.5 Hz

Spectral analysis of such irregular data is not possible with Fast Fourier Transform (FFT), which computes a Fourier decomposition under the assumption that samples are equispaced. Attempts to ‘repair’ the data, *e.g.*, with interpolation, obviously introduce new sources of uncertainty, and this renders the most common spectral analysis methods inappropriate.

However, the Lomb-Scargle periodogram approach (also known as least-squares spectral analysis), derived by Lomb [97] and later validated with a mathematical proof by Scargle [141], accurately handle non-equispaced data by, effectively, fitting a sine wave and estimating its frequency spectrum.

In particular, Fast Calculation of the Lomb-Scargle Periodogram (FASPER) [126] employs four parameters: the vector time series along with the time coordinate of each sample, an output gain and an oversampling parameter to control resolution of the computed spectrum. FASPER computes the significance level for each of a discrete set of frequencies.

RRACE uses FASPER to find the spectrum of the overall movement of the device. We then make the key assumption that cadence is the most significant frequency peak in the spectrum for a given computational window. We define our algorithm’s latency as half the window length – *e.g.*, a 4 second window has a latency of 2 seconds.<sup>3</sup>

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<sup>3</sup>Although it may be possible to improve the performance of our algorithm through signal pro-

### 4.3.3 Pseudocode

Pseudocode for our implementation is shown in Figure 4.1. We obtained the highest accuracy using 0.25 and 4.0 for FASPER’s output gain (“hifac”) and oversampling (“ofac”) parameters, respectively.

```
function RRACE():
    (timestamps, xs, ys, zs) := get_accelerometer_values(from 4s ago to now);
    n := length(timestamps);
    magnitudes := new array of length n;
    for i := 1 to n do
        magnitudes[i] := sqrt(xs[i]^2 + ys[i]^2 + zs[i]^2);
    size := 128*n;
    hifac := 0.25;
    ofac := 4;
    frequencies := fasper(timestamps, magnitudes, size, ofac, hifac);
    cadence := most_powerful(frequencies);
```

Figure 4.1: RRACE Pseudocode.

### 4.3.4 Android-Based Validation Platform

The results of Section 4.4 are based on data from up to six simultaneously-worn Google Nexus One smartphones running Android OS version 2.3.4 (Gingerbread). Our main application was implemented in Java, the primary programming language for Android development. Numerical programming algorithms (including FASPER) were implemented in C for speed benefits and because of readily-available implementations [126]. We used the Java Native Interface (JNI) to connect the two languages.

## 4.4 Experimental Validation of RRACE

In laying out RRACE’s formal validation, we first summarize a pilot study which informed our subsequent methodology. We then describe our full study’s walking task, apparatus, and measurement; and its design, metrics, analysis, and subjects.

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cessing, *e.g.*, by employing a smoothing filter, for the current analysis we did not use any filter or other processing components other than the parts we describe here. This permitted us to make the fairest comparison possible to other algorithms, since we were not aware of what optimization they had undergone.

Next, we present the results of the analysis for the optimally configured (4 second window) RRACE and compare it with other RRACE variants. Finally, we measure the power consumption of our algorithm and compare it with similar Android apps in the market.

Our dataset is available at: <http://www.cs.ubc.ca/labs/spin/data/>.

#### 4.4.1 Treadmill-based Pilot Validation

Before conducting our full outdoor experiment, we built confidence in our general approach (algorithm and smartphone implementation) with a preliminary study based on four participants (one female) who volunteered without monetary compensation out of interest in the research. The setup consisted of a treadmill, the three Google Nexus One smartphones available at the time, and a PC x86-64 for manual logging of footfalls. Smartphones were synchronized with the PC; each phone recorded accelerometer signals (average sampling frequency = 24.8 Hz) and estimated cadence using RRACE in realtime.

Subjects walked for 15 minutes at a selection of speeds chosen to represent slow to fast walking based on similar studies and pedestrian speeds [43, 85], while wearing smartphones on 3 of the 6 LOP sites at a time, randomly selected each trial. They then walked for another 15 minutes wearing the phones on the other three locations. For both segments, they were instructed to adjust their walking speed to keep up with the changes in treadmill speed, but given no instructions as to step frequency.

We assessed accuracy of cadence measurement relative to the manually recorded step interval ( $T_m$ ). Our primary metric – Error Ratio (ER) – was thus the ratio of RRACE’s measurement “error” (the difference between the frequency measurement produced by RRACE,  $F_a$ , and the reference frequency,  $F_r$ ) to the reference frequency:

$$ER = \frac{|F_a - F_r|}{F_r} \tag{4.1}$$

where



$$F_r = \frac{1}{T_m}$$

**Pilot Study Results:** In an Analysis of Variance (ANOVA) on ER, our independent variables were LOP (6 sites), Speed (10 speeds ranging from 0.45m/s to 1.65m/s), and Window Size (2 lengths: 4 s and 8 s). We used a significance level of 0.05, applying a Bonferroni correction to counteract the multiple comparisons problem.

Location had a significant effect on ER. *Front pocket* (mean = 6%, SD = 11%), *belt* (mean = 14%, SD = 30%), *arm* (mean = 15%, SD = 30%), and *bag* (mean = 15%, SD = 32%) were much more reliable than *back pocket* (mean = 30%, SD = 38%) and *hand* (mean = 31%, SD = 27%). Speed also had a significant effect on ER. RRACE had a lower ER at higher speeds across all LOPs except *hand*. *Arm*, *bag*, *belt* and *front pocket* reached their low ER at a much lower speed than did *back pocket*. Surprisingly, *hand* did better at lower speeds. The impact of window size was statistically significant but of a small numerical value, with 8 s window outperforming 4 s window.

The pilot study confirmed general accuracy for our approach and suggested a better choice of factors for use in a more naturalistic outdoor-walking study. Specifically, because 4 s and 8 s window sizes both produced good performance with minimal difference, we concluded that the accuracy of window sizes larger than 4 s is not worth the extra latency and we decided to try smaller window sizes for comparison. We reduced the number of speed levels to five.

#### 4.4.2 Primary Outdoor Walking Task and Measurement Apparatus

The primary experiment to validate RRACE was run on a concrete sidewalk in an open area on a university campus, with no nearby buildings to block GPS signals.<sup>4</sup> Subjects were asked to walk twice at each of five different speeds, and instructed with the definitions provided in Table 4.1. We further instructed all subjects that ‘leisurely’ walking speed meant their slowest normal walking speed, and ‘typical’ walking speed is their usual walking speed. Allocation of walking speed order was

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<sup>4</sup>While GPS data were collected for possible use in validation, RRACE does not use GPS data itself.

randomized.

We note that subjects’ walking speed and cadence were not expected or required to be perfectly consistent (either within or between subjects) for measuring accuracy of cadence detection. Our goal was to observe walking at a larger variety of speeds for every individual, and this loosely controlled mechanism allows a more finely resolved spectrum of actual speeds; meanwhile, this allowed a large dataset, mitigating the effect of imbalances and imperfections.

**Table 4.1:** Walking Speeds During the Experiment.

Label	Definition	Mean (m/s)	SD
Speed -2	leisurely (slowest) walking speed	1.14	0.22
Speed -1	slower than typical but faster than leisurely	1.34	0.14
Speed 0	typical walking speed	1.52	0.08
Speed 1	faster than typical but slower than the fastest speed	1.67	0.12
Speed 2	fastest walking speed	1.95	0.12

**Apparatus:** The experimental setup consisted of six Google Nexus One smartphones, an external GPS receiver connected to one of the phones via bluetooth, our *reference* cadence measurement consisting of two shoe-mounted Force Sensing Resistor (FSR) sensors [72] to detect footfalls and connected to a Bluetooth-enabled Arduino board, developed by SmartProjects (Strambino, Italy) [150], two laptops (one for logging trials and a second, a small netbook, to log footfalls sent from the Arduino board via Bluetooth), a backpack, a stop watch, and two flags for experimenters to send timing signals to each other. The study required three experimenters to run.

Prior to the experiment, subjects were asked to wear pants with front and back pockets but pocket locations were not controlled. The six phones and the Arduino board were synchronized with the main computer at the start of the experiment. One of the phones, the GPS receiver, netbook, and Arduino were put in the backpack (*bag*). The bag had a filled weight of approximately 2 kg. See Table 4.2 for general phone locations, which were chosen as the places people used most frequently for their mobile phones while commuting [28].

**FSR Footfall Detection:** We used timestamped FSR data as our *reference* footfall

detection method:

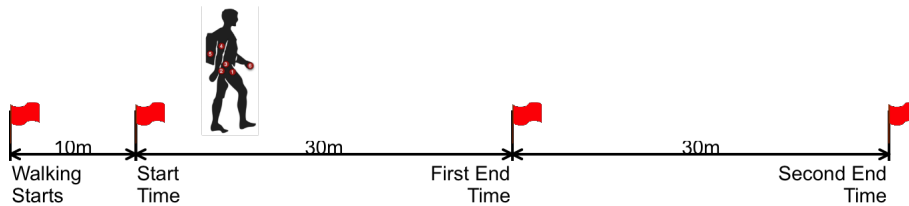
$$ER = \frac{|F_a - F_r|}{F_r} \quad (4.2)$$

where

$$F_r = \frac{1}{T_{FSR}}$$

FSRs are ideal for detecting changes in force. We placed an FSR force sensor, by Interlink Electronics (Camarillo, CA, USA) [72], inside each shoe (to measure the force exerted by subjects' feet and compare it with a threshold), and connected both to the Arduino. The Arduino timestamped the FSR readings (avoiding impact of Bluetooth latency) and sent them on to the netbook via Bluetooth. The footfall detector system was calibrated and verified for each subject at the beginning of the experiment. To analyze the data, we used the median of the last three intervals of each of the two feet ( $T_{FSR}$  in Equation 4.2) to filter errors caused by false positives (extra footfall detected) or false negatives (footfall missed).

***Trial Length and Speed Measurement:*** We wished to collect 20 seconds of walking data for each trial (twice the length of our largest window size with a 25% safety margin) and compute step frequency every 200 ms. We asked subjects to walk a known distance, either 30m or 60m (marked by small flags along the walkway), depending on whether 20 seconds had elapsed by the time the 30m point (first end time) had been reached (Figure 4.2). Timespan was manually recorded via stopwatch.



**Figure 4.2:** Experiment walkway, start and end points.

### 4.4.3 Experiment Design, Metrics, and Subjects

The design was within-subjects repeated-measures, with independent variables of *window size*, LOP, and *speed condition* (Table 4.2). The five speed conditions and their repetitions (10 trials) were randomized.

**Table 4.2:** Experiment design

<i>Factor</i>	Number of Levels	Factor Levels
Window Size	4	1, 2, 4, or 8 seconds
LOP	6	<i>back pocket, bag (backpack), dominant hand (held), front pocket, hip (mounted on belt), upper arm (mounted)</i>
Condition	5	<i>typical (0), fastest (2), leisurely (-2), faster than typical (1), slower than typical (-1)</i>
Repetition	2	first time, second time

**Metrics and Analysis:** We assessed RRACE’s accuracy by comparing it to our shoe-located force sensor reference (Section 4.4.2). As in the pilot, our primary metric was ER (Equation 4.1 in Section 4.4.1). We conducted our analysis with Generalized Linear Models (GLM), using unpaired Z-test comparisons for post-hoc analysis and  $p = 0.05$  significance, again applying a Bonferroni correction. Note that for sample sizes as large as our dataset, Z-test produces the same result as a t-test. Also, we report differences between effect levels as z-scores, and because z-scores are normalized by standard deviation, differences between means in our analysis are analogous to Cohen’s  $d$  statistics of effect size.

**Subjects:** Eleven individuals (6 female and 5 male), aged 21 – 30 years ( $mean = 25.2$ ,  $SD = 3.3$ ), 155 – 179 cm tall ( $mean = 165.9$ ,  $SD = 7.0$ ), and weighing 46 – 80 kg ( $mean = 59.1$ ,  $SD = 10.0$ ) volunteered. No subjects had physical impairments.

**Speed / Frequency Relationship:** As a basic check for our measurements we verified a correlation between walking speed and cadence ( $r = 0.84$  using Pearson’s Correlation), which is consistent with [67].

#### 4.4.4 Results for Outdoor Validation of 4 Second Window RRACE

We chose the 4-second window RRACE as our analytical baseline, and describe its analysis first: both theoretically and in our pilot, 4 seconds is enough to detect a wide range of walking cadences. We then present results from alternative window sizes. Because the phones were prone to dropping data (14%), we used GLM for its robustness to this situation.

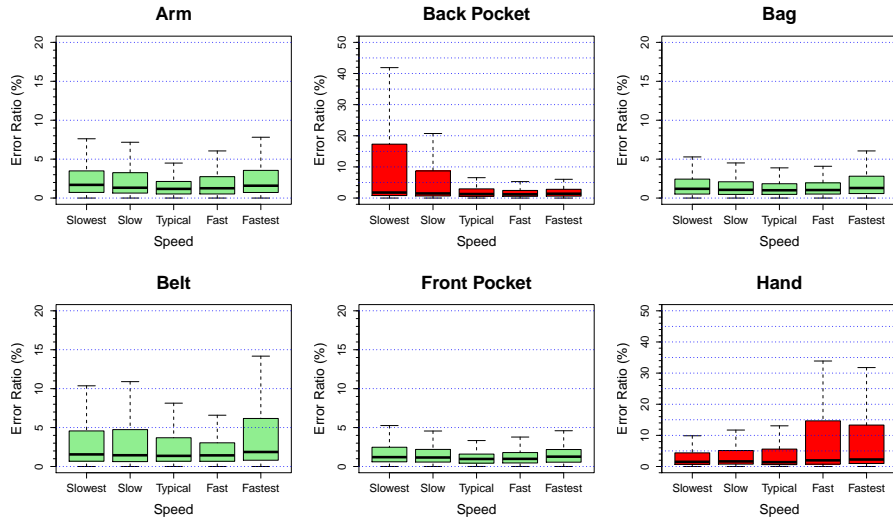
**Main Effects:** LOP has a significant effect on ER. Results were consistent with our pilot: *front pocket*, *belt*, *arm*, and *bag* (light-green box plots of Figure 4.3) are much more reliable than *back pocket* and *hand* (dark-red box plots of Figure 4.3). Speed condition also has a significant effect on ER; ER is generally lower at the typical and fast speed and higher at the slowest and the fastest speed.

**Interaction Effects:** Both LOP / speed condition and LOP / window size on ER interact significantly. *Arm*, *bag*, and *front pocket* ER remain consistently below 5% under all speed conditions, with their minimum at the middle (typical) speed. *Belt* produces lowest ER at the typical speed and largest ER at the fastest speed. *Back pocket* produces lower ERs at higher speeds and *hand* produces lower ERs at lower speeds (Figure 4.3). As we will see in Section 4.4.5, the interaction between LOP and window size does not affect our general conclusions about LOPs.

#### Quantitative Comparisons

**Location on Person (LOP):** Table 4.3 compares ER as a function of LOP – four out of six locations have an ER of 5% or below. *Front pocket* and *bag*, with the lowest ERs, significantly outperform the other locations. For example, *arm* has an ER of 3.6% on average and is 0.3% different from *front pocket* while *bag* and *front pocket* are not significantly different from each other.

This accuracy is approximately the same as the best reported elsewhere and has proved acceptable for most applications [43, 106]. As noted earlier, it is not currently possible to make a direct comparison (*i.e.*, based on running the algorithms on the same dataset, or confirmation that the datasets / experimental conditions are fully comparable) with other reported results given the level of implementation detail available. However, to the best of our knowledge the comparison is conser-



**Figure 4.3:** ER (ER) as a function of Speed Condition for 4-Second Window RRACE. Dark-red boxplots have a larger range for ER. The boxplot’s central bar indicates sample median.

vative: we asked RRACE to do the same or harder task, in that our setup was far less constrained.

**Table 4.3:** ER differences by LOP for *four-second window* RRACE through an unpaired Z-test.

The second column contains the mean ER of each LOP; remaining cells contain the difference between two LOPs where the difference is significant. The differences are the maximum possible while maintaining statistical significance, and thus are less than the distance of ER means from each other. A large value means larger distance between ERs.

LOP	ER (%)	Difference from				
		Front Pocket	Bag	Arm	Belt	Back Pocket
Front Pocket	2.8	-	-	-	-	-
Bag	3.1	not sig	-	-	-	-
Arm	3.6	0.3	0.1	-	-	-
Belt	5.5	2.2	2.0	1.4	-	-
Back Pocket	7.9	4.5	4.3	3.7	3.0	-
Hand	11.4	7.8	7.6	7.1	5.2	2.6

**Speed Condition:** Figure 4.3 shows that ER decreases as speed increases only when the phone is placed in *back pocket* and the opposite happens when the phone is held in *hand*. However, the differences among different speed conditions are

not very obvious for other LOPs in the figure. We can exclude those two LOPs and quantitatively compare speed conditions for the other LOPs; if we do so, we will see that ER is lower at the typical and fast (one level above typical) speed and generally highest at the slowest and/or fastest speed conditions (Table 4.4).

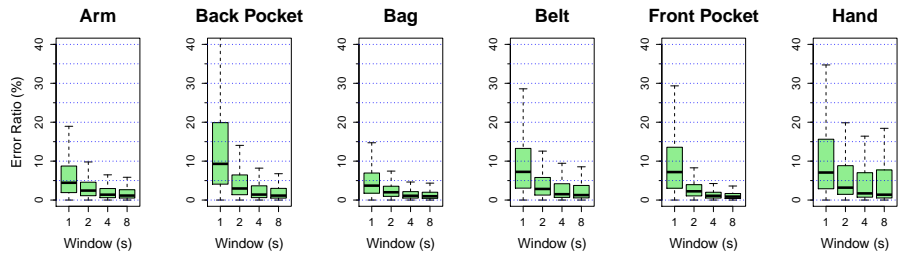
**Table 4.4:** RRACE ER differences by speed condition for 4 LOPs with a *four second window* (unpaired Z-test). *Hand* and *back pocket* – the inconsistent LOPs with more obvious reaction to speed – are excluded to focus on the effect of speed in the absence of the interaction effects and on the more similar LOPs. See Table 4.3 for more information.

<i>Speed Condition</i>	<i>ER (%)</i>	Difference from			
		(0)	(1)	(-1)	(2)
Typical (0)	2.5	-	-	-	-
Fast (1)	2.8	0.04	-	-	-
Slow (-1)	3.4	0.6	0.3	-	-
Fastest (2)	4.0	1.1	0.8	0.2	-
Slowest (-2)	6.3	3.2	3.0	2.3	1.7

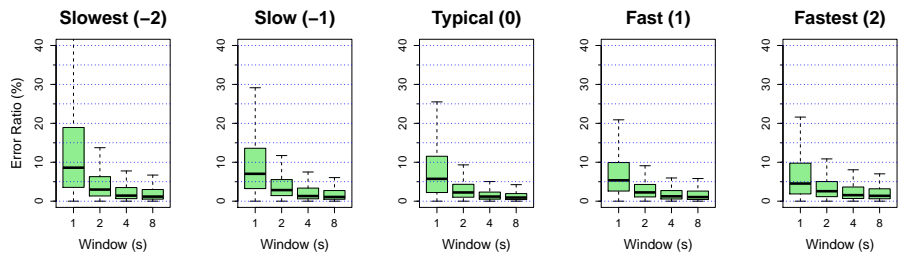
#### 4.4.5 Analysis of The Effect of Window Size on RRACE

Four-second and eight-second processing windows produced similar ERs, consistent with our pilot results (Figures 4.4, 4.5, and Table 4.5). While the ER of a one-second window is double that of four or eight seconds, the two-second window is only 1% (significant) different from four and eight-second windows, and may be usable in some circumstances (Table 4.5). As shown in Figure 4.4, increasing window size reduces ER for all LOPs but has a smaller effect on locations with lower ER in general. By comparing Table 4.3 (ER of LOPs for four-second window RRACE ) with Table 4.6 (ER of LOPs for all variations of RRACE ) we see that window size only affects the rank of *front pocket* among other LOPs; *front pocket* is not the best LOP when we choose smaller window sizes. Other five LOPs stay in the same relative order when we change window size.

As anticipated, the effect of increasing window size on reducing ER is more noticeable at lower speeds (Figure 4.5). Since smaller windows capture fewer steps than larger windows, with decreasing speed the chance of capturing enough steps is reduced. In effect, increasing window size compensates for the effect of slowing down.



**Figure 4.4:** ER is a function of Window Size per each LOP for all Speed Conditions lumped.



**Figure 4.5:** ER is a function of Window Size per each Speed Condition for all LOPs lumped.

#### 4.4.6 Power Consumption

We used PowerTutor [125] to measure RRACE’s power consumption on a Samsung Galaxy Nexus smartphone running the Android 4.1.1 Jelly Bean operating system, and compared it with Endomondo [33], a sport tracking app, which is claimed to be the highest rated app of its kind on Android, Runtastic Pedometer [137], a pedometer app that uses accelerometers to count steps, and Angry Birds, the famous game (Table 4.7).

**Table 4.5:** ER differences by window sizes of RRACE, with walking speed and LOP lumped. Window sizes are ordered by increasing ER mean. See Table 4.3 for more information.

Window Size	ER (%)	Difference from		
		8 Seconds	4 Seconds	2 Seconds
8 Seconds	5.8	-	-	-
4 Seconds	5.8	not sig	-	-
2 Seconds	7.1	1.1	1.1	-
1 Second	11.5	5.4	5.4	4.1



**Table 4.6:** RRACE ER differences by LOP for all window sizes and walking speeds (unpaired Z-test). Locations are ordered by increasing ER mean. See Table 4.3 for more information.

LOP	ER (%)	Difference from				
		Bag	Arm	Front Pocket	Belt	Back Pocket
Bag	4.1	-	-	-	-	-
Arm	4.8	0.5	-	-	-	-
Front Pocket	5.5	1.2	0.4	-	-	-
Belt	7.1	2.8	2.0	1.3	-	-
Back Pocket	10.5	6.1	5.3	4.6	3.0	-
Hand	12.8	8.3	7.6	6.9	5.3	1.9

Like most activity measurement algorithms, RRACE does not require the display to be on; but for consistency, all of these apps were compared with screen on. PowerTutor is able to distinguish between LCD power usage, which Table 4.7 shows is similar for all of them. CPU power usage varies: RRACE uses  $10\times$  the CPU power of Endomondo,  $5\times$  more than Runtastic Pedometer, and is comparable to Angry Birds.

With the screen off, our algorithm will consume considerably less power than mobile games even before improving the CPU efficiency. Until now, our development has focused on proving accuracy rather than power efficiency, so the low power consumption of other activity measurement apps is promising in terms of what RRACE can achieved with optimization, *e.g.*, with methods such as “code offload” [27] and “ $\mu$ Sleep” [13].

**Table 4.7:** Power consumption.

App Name	Duration (s)	Average Usage (mW)	LCD Usage	CPU Usage
RRACE	361	772.85	528.53	244.32
Endomondo	308	555.52	529.87	25.65
Endomondo (no GPS)	369	548.78	530.08	18.70
Runtastic Pedometer	322	575.47	521.74	53.73
Angry Birds	559	735.78	516.00	225.33

## 4.5 Comparing RRACE with a Threshold-based Time-domain Algorithm

As detailed in Section 4.2, the many pedometers available commercially use proprietary algorithms that have not been released to the public. We therefore compared our frequency-based algorithm to MPTrain’s algorithm [115]. MPTrain uses two low-pass filters. One removes noise in the original accelerometer signal, producing a smoothed signal; the second has a lower cutoff frequency, and its output is used as a dynamic threshold. Footsteps are detected when the smoothed signal crosses the dynamic threshold from above to below (Figure 4.6). Because the MPTrain accelerometer is required to be situated on the user’s torso and oriented to detect accelerations in the superior-inferior axis, it detects footsteps on both feet. Foot falls are translated to instantaneous (*i.e.*, sampled) Steps per Minute (SPM) using the following formula:

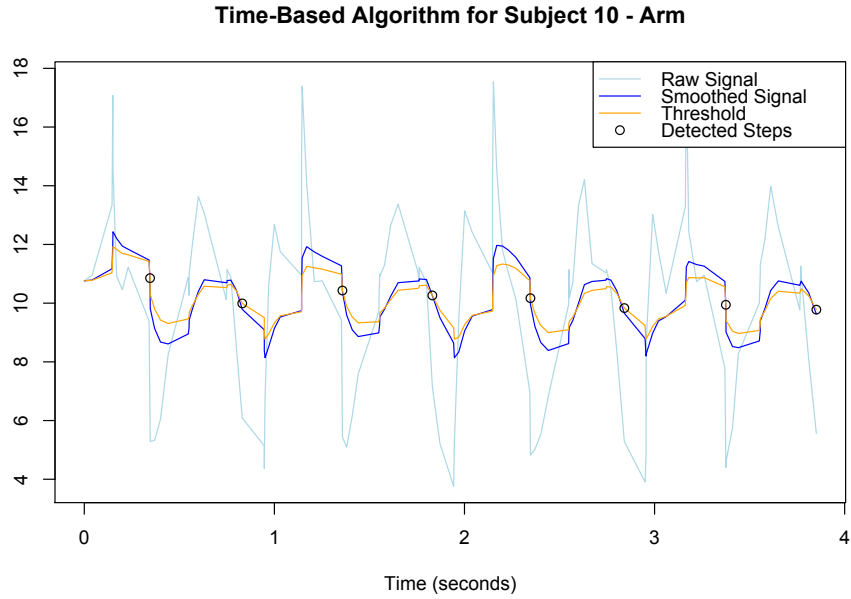
$$SPM_i = (int) \frac{60.0 \times SamplingRate}{\#SamplesSinceLastStep} \quad (4.3)$$

Finally, the MPTrain algorithm applies a median filter to the instantaneous SPM to calculate estimated SPM. The MPTrain study reported a uniform sampling rate of 75 Hz for accelerometer data, achieved with an external chest-mounted sampler. The authors report that cadence measurement accuracy is comparable to those found in commercial pedometers by [106], but provide no specifics.

### 4.5.1 Implementation of Time-based Algorithm for Comparison

We reconstructed parameterizations for the MPTrain algorithm, since details were not reported for either of the low-pass filters, and no window was given for the median filter. We also accommodated the variable sampling rate found in smartphones, and measured cadence in Steps per Second (SPS) instead of SPM to compare it with RRACE.

Finally, given that we do not have a sensor in a known orientation, we also consider each of four different axes in our analysis:  $x$ ,  $y$ ,  $z$ , and  $m$  (the magnitude of the vector, *i.e.*,  $m = \sqrt{x^2 + y^2 + z^2}$ ).



**Figure 4.6:** Example of the MPTrain time-based step detection algorithm. The y-axis shows the L-2 norm (magnitude) of the accelerometer signal.

Two low-pass filters (accelerometer data smoothing and dynamic threshold) employ parameters  $\alpha$  and  $\beta$  ( $\beta < \alpha$ ), which were trained on our data (Section 4.5.2). For efficiency and simplicity, we implemented these as Exponentially-Weighted Moving Averages (EWMA). An EWMA is defined as follows:

$$S_i = \alpha x_i + (1 - \alpha)S_{i-1} \quad (4.4)$$

where  $S_i$  is the  $i$ -th smoothed (low-passed) value,  $x_i$  is the  $i$ -th raw accelerometer value, and  $\alpha$  is the smoothing parameter ( $0 \leq \alpha < 1$ ).

As for MPTrain, steps are detected when the smoothed signal crosses the dynamic threshold from above to below. The difference between step times is used to calculate instantaneous cadence by the formula:

$$\text{Cadence} = 1/\text{CurrentDifferenceBetweenSteps} \quad (4.5)$$

For example, if the two previous footsteps were detected at  $\text{StepTime}_i = 100$  ms and  $\text{StepTime}_{i+1} = 600$  ms and we wanted the instantaneous cadence at any time  $t \geq 600$  ms, we would compute  $1/(600 - 100) = 0.002$  steps per millisecond, or 2.0 SPS. Final cadence estimates were the average of each instantaneous cadence estimate and one previous estimate (*i.e.*, a 2-sample smoothing filter).

#### 4.5.2 Tuning of the Time-based Algorithm

To compare the MPTrain time-based algorithm as favourably as possible to RRACE, we optimized the low-pass filter smoothing parameters  $\alpha$  and  $\beta$  (Section 4.5.1) for several data subsets involving different combinations of subjects and LOP:

- All data (all subjects and LOPs): 1 set
- Each subject (over all LOPs): 11 sets
- Each LOP (over all subjects): 6 sets
- Each subject-LOP combination (*e.g.*, Subject 1, Arm) minus 9 (missing data):  $11 \times 6 - 9 = 57$  sets

This thorough search thus used 75 parameterizations of the time-based algorithm. During analysis (below), data were only scored on the dataset on which it was trained. This represented a best-case scenario of an algorithm trained for a certain individual and/or LOP, which could occur in real-world use cases with one individual using a personal device in a consistent way.

Within a dataset, we used a uniform search for the best combination of smoothing parameters ( $\alpha$  and  $\beta$ ) with a granularity of 0.05 (*i.e.*,  $\alpha \in \{0.05, 0.1, \dots, 1.0\}$  and  $\beta \in \{0, 0.05, \dots, 1.0\}$ ), one of the three axes or magnitude ( $\gamma \in \{x, y, z, m\}$ ), as well as four scaling factors ( $\delta_{x,y,z} \in \{\frac{1}{2}, 1, 2, 4\}$  for individual axes and  $\delta_m \in \{\frac{1}{4}, \frac{1}{2}, 1, 2\}$  for magnitude; scaling factors accommodate harmonics by scaling the computed cadence). The best of all these combinations for each dataset was determined by having the lowest mean squared ER by comparing to the FSR gold

standard. The scaling factors scale the calculated cadence; for example if the user walks at 1.5 Hz and the time-based algorithm calculates a cadence of 0.75 Hz (*i.e.*, detects either left or right steps), a scaling factor of 2 would fix this ( $0.75 \times 2 = 1.5$ ).

### **Analysis of Time-based Algorithm**

We found it was not possible to train the time-based algorithm to work on all LOPs and for all subjects with an ER below 5%; the minimum attained was ER = 74%. The time-based algorithm for all LOP on one subject reached ER = 18%, but this was only for the best-case scenario.

Tuning the time-based algorithm for one best-case LOP on all subjects was more feasible: this achieved ER = 12% for *bag*. If we tune the algorithm for one LOP of each subject we may even get a lower ER; when tuned for Subject10's *arm*, the algorithm reached ER = 7.8% (Table 4.7). In the next section we will show that these results are not nearly as good as the performance of RRACE with ER = 5.8% for the 8s window variant.

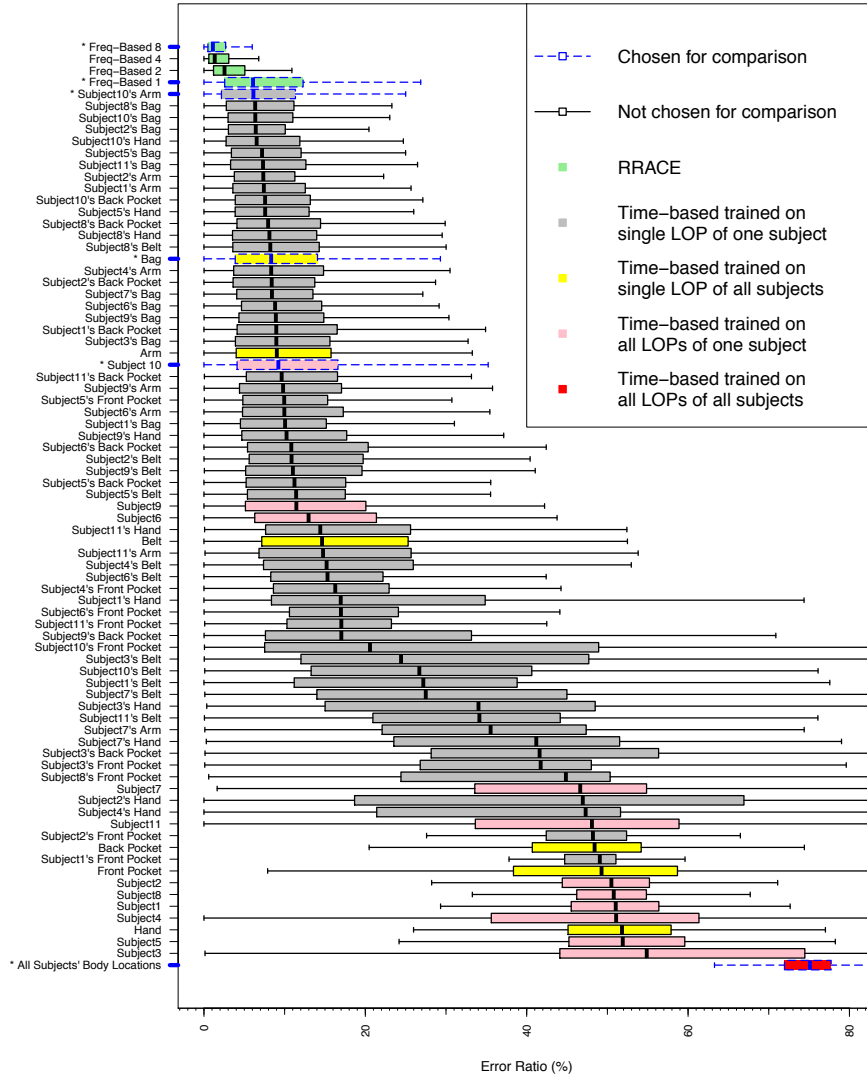
### **Comparisons with Frequency-based Algorithm**

Figure 4.7 shows boxplots of ER of all the RRACE and time-based algorithm variants ordered by the median of ER. We divided them into five categories as identified in the figure's caption, differing by algorithm and breadth of training set, where a more specific (but unrealistic) training set generally leads to better performance in this test.

Because it is unproductive to compare each of these algorithms with the rest, we have chosen the best of each category in addition to the worst-case RRACE variant (one-second window) which are marked by blue ticks and blue dashed-line box plots on Figure 4.7. This is a highly conservative comparison which tends to favor the time-based algorithm. We used the same data for verification of each time-based algorithm that was used for their training and secondly, the ER of all versions of the frequency-based algorithm is measured across all LOPs of all subjects. RRACE was not trained or tuned in this comparison.

Thus, the single "fair" comparison is between either version of RRACE (green in Figure 4.7), and the time-based algorithm trained on *all* subjects and *all* LOPs

### All Algorithms



**Figure 4.7:** ER compared for all algorithm variants and ordered by median. (a: GREEN) 4 window sizes of RPACE (first four); time-based algorithm trained on: (b: RED) all subjects' LOPs (last one), (c: PINK) all LOPs of each single subject, (d: YELLOW) one LOP of all subjects, and (e: GREY) single LOP of one subject. Algorithms chosen for quantitative comparison are marked by blue ticks and blue dashed-line boxplots.

(red). Table 4.8 summarizes these comparisons, but in order of mean rather than median; thus subject10's *arm* comes after the 1-second RRACE in the figure but before it in this table.

The best of time-based categories — Subject10's *arm*, *bag* (across all subjects), Subject10 (all body locations), and all subjects' body locations — and the 8-sec and 1-sec variants of RRACE appear on the first column of Table 4.8. Their respective ERs are listed in the second column. It is statistically incorrect to compare these values without testing the statistical significance of their difference. Therefore, we used unpaired Z-tests (with Bonferroni correction for multiple comparisons) to (a) test the statistical significance of the difference between each two algorithms (one from the first column vs another one from the third to seventh column of the second row), and (b) measure the maximum difference while maintaining statistical significance which does not apply to pairs that are not significantly different such as *bag* vs 1-sec RRACE; this also applies to Tables 4.3, 4.4, 4.5, and 4.6.

In particular, the difference between the best variant of RRACE and the bests of all categories of time-based algorithm, 1.2, 5.5, 10.2, and 67.5 presented on rows 4, 6, 7, and 8 (row of Subject10's *arm*, row of *bag*, row of Subject10, and row of all subjects' body locations) and 3rd column (column of 8-Sec RRACE) are important to us; these values show that RRACE has a much lower ER than any of the time-based algorithms and this difference is statistically significant.

## 4.6 Discussion

The goal of this research was to develop a cadence measurement algorithm for accelerometer-equipped mobile phones. We required this algorithm to be robust and work out-of-the-box with an ER of 5% or less (comparable to Yang et al.'s *waist-mounted* cadence measurement device [174] and MPTrain of Oliver & Flores-Mangas [115]). First, we will review the nature of RRACE's error, its performance on different LOPs and robustness to subject differences, and compare it with the time-based algorithm. Then we will examine its main weakness, and finally we will discuss the best choice for window size.

**Table 4.8:** Unpaired Z-test comparison of error ratios of the best and the worst versions of the frequency-based algorithm and the best of each category of time-based algorithm. Algorithm variants are ordered by increasing ER mean. See Table 4.3 for more information.

Algorithm	ER (%)	Difference with				
		8-Sec RRACE	Subject10's Arm	1-Sec RRACE	Bag	Subject10
8-Sec Window RRACE (a)	5.8	-	-	-	-	-
Subject10's Arm (e)	7.8	1.2	-	-	-	-
1-Sec Window RRACE (a)	11.5	5.4	2.9	-	-	-
Bag (d)	11.9	5.5	3.2	not sig	-	-
Subject10 (c)	17.9	10.2	8.1	4.6	4.0	-
All Subjects' Body Locations (b)	73.5	67.5	65.0	1.8	60.9	53.7

#### 4.6.1 The Nature of RRACE's Error

A small number of outliers are responsible for some of the error in RRACE's readings. These are of two types: (a) random readings as a result of irregularities in the signal, and (b) harmonic readings which happen when the main frequency component gets smaller than its harmonics. These outliers may be avoided by filtering the outcome of RRACE. The rest of the error is caused by hardware measurement error and delay from the 4 second window.

#### 4.6.2 RRACE Meets Criteria for 4/6 of Tested Locations; Time-Based for 0/6

Movement at four LOPS (*arm, bag, belt, and front pocket*) contain sufficient consistent information for RRACE to make accurate estimates and RRACE does not need to be calibrated in order to work there. They each achieve a 3–5% ER, satisfying the criteria laid out above.

In contrast, the time-based algorithm was highly sensitive to LOP. It was almost impossible to tune the time-based algorithm for three of the LOPS, *front pocket* among them. The LOP that fit the time-based algorithm the best was *bag* with almost double the ER of the 8-second and 4-second window RRACE.



### **4.6.3 RRACE is Robust to Subject Differences**

The time-based algorithm was very sensitive to subject differences. It could not be trained to work on all LOPs of all subjects, and when trained on single LOPs, only 12% was achieved, in only one location (*bag*). Because it was calibrated by subject, its present tuning would not work on subjects outside our experiment with no adjustment. However, RRACE achieved much lower ER for all subjects with no prior tuning to compensate for subject differences.

### **4.6.4 RRACE is Sensitive to Very Slow Speeds**

Our outdoor validation results showed that, like other pedometers, RRACE is sensitive to speed. The highest ER belongs to the slowest speed with  $ER = 6.3\%$ . We attribute this worsened performance to two possible causes:

(a) At lower speeds, walking cycles take longer and fewer cycles are captured in a fixed window size. As anticipated, this weakens RRACE. Mitigation requires use of a larger window size, *e.g.*, by dynamically changing the window size to fit the speed.

(b) Walking becomes less autonomous and more irregular when subjects are asked to walk at very low speeds, especially because users can easily choose to walk as slowly and irregular as they want, while at high speeds step interval is bounded by the subject's physique.

The time-based algorithm is less affected by walking speed because it just detects single steps, no matter how irregular or distant from each other they are. Thus one practical approach might be to shift to a time-based algorithm at low speeds.

### **4.6.5 RRACE Window Length of 4 Seconds is Best**

Our results showed that highest accuracy (lower ER) is achieved at larger window sizes. The difference in ER is substantial for 1 vs 2-second windows, and for 2 vs 4-second windows, but not for 4 vs 8 seconds. A 4-second window size seems the ideal length among our candidates as a compromise between responsiveness and accuracy.

## 4.7 Conclusion and Future Work

In this chapter we introduced a new algorithm for measuring cadence through a frequency-domain analysis of accelerometer data from smart phones, called RRACE. This algorithm's advantages are strong robustness to location on body, orientation, and to individual physiological parameters, resulting in exceptional usability and suitability for a broad range of consumer-type applications.

We also presented an experiment design to verify our and other algorithms. Our user-based validation showed that RRACE performs well under different speed conditions, providing 5% or lower error for four of the six common LOPs examined: *front pocket*, *bag*, *arm* and *belt*, consistent with previous work in a single location [174], and producing 8% and 11% for the other two: *back pocket* and *hand*. RRACE's primary weakness is a drop in performance for slow and irregular walking, a flaw which can be mitigated by dynamically adjusting the window size to maximize accuracy at the cost of more latency, and/or switching to a time-based algorithm at slow speeds.

We compared RRACE with a state-of-the-art published time-based algorithm which we tuned in every way possible; our highly conservative comparisons show that RRACE is substantially more accurate than the time-based algorithm tuned for any subset of the data. Our results show that RRACE is also superior to the time-based algorithm in terms of independence from LOP and robustness to user differences. The exception is for very low and/or irregular speeds, situations which many applications of a cadence detection method might classify as a different gait and analyze using a different algorithm. We also plan to extend comparisons to include autocorrelation of time-based techniques, which may share some of the advantages of a frequency based approach.

As well, our algorithm provides general guidelines for window size and robust spectral analysis. This information can be used to inform solutions to more complex realtime gait analysis problems, such as activity detection for fitness or rehabilitation applications, or individual gait identification for mobile security.

We are continuing to improve our algorithm. Some avenues likely to further increase its performance are to reduce estimation outliers by using smart filters and adjust window size based on current cadence. We will also look into reducing

power consumption of our algorithm by reducing sampling and CPU usage when the subject is in low activity mode. Finally, we look forward to deploying RRACE in the real world: we are engaged in employing cadence to measure other useful information about gait such as stride length and type of gait, and exploring deployment in a variety of real applications [143].

## **4.8 Acknowledgment**

This work was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) and the GRAND NCE. User data were collected under University of British Columbia's Research Ethics Board approval H01-80470.

## Chapter 5

# Susceptibility to Periodic Vibrotactile Guidance of Human Cadence

*If everything seems under control, you're not going fast enough.*  
— Mario Andretti

In this chapter we<sup>1</sup> introduce a new guidance method that employs periodic vibrotactile cues to help users walk at a desired speed. We also explore walker's *susceptibility* to Periodic Vibrotactile Guidance (PVG): specifically, adjustments of their stride frequency in response to cues that are clearly perceived; and finally, how long users can maintain their stride frequency after the guidance cue stops.

While wearing a vibrotactile display on one wrist, each participant was given five vibrotactile tempos, logarithmically spaced across the participant's walking frequency range. We measured stride frequency, and compared it with cue tempo under conditions that varied cue tempo and presence / absence.

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This chapter appears with minimal modifications in: [76]

- I. Karuei and K. E. MacLean. Susceptibility to periodic vibrotactile guidance of human cadence. In *Haptics Symposium (HAPTICS), 2014 IEEE*, pages 141–146, 2014

<sup>1</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.

Our results suggest that most individuals (here, 13 out of 15) can synchronize their cadence with a vibrotactile cue with 95% accuracy (mean error, all participants: -1.5%,  $SD = 8.1$ ) for a guidance tempo within their physical ability. Once a tempo was matched, walkers could maintain it for at least 30 seconds after the cue was turned off, showing promise for intermittent guidance as a solution to stimulus adaptation and annoyance.

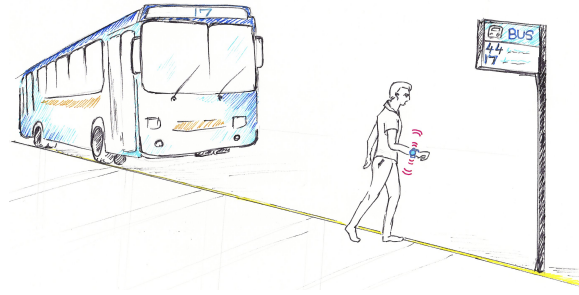
This finding informs design of spatiotemporal guidance systems, by showing how the informationally narrow but nevertheless underused haptic channel may have utility in guiding pedestrians' speed, without a need to learn abstracted signals, and through a continuous control system.

## 5.1 Introduction

New technologies emerge daily that aim to use sensing and computation to assist in our daily activities: task and time management, navigation and location services are but a few. Many are framed as guidance tools: they can save us time or improve our performance in some task (*e.g.*, walking in an unknown neighborhood) by providing immediate information or by making a task (*e.g.*, finding the nearest coffee shop) easy enough to be done in parallel with another.

However, this potential is often undermined by usability challenges, with one of the most crucial being sensory load. Whatever the communication channel, signals deployed at a conscious level are likely to be intrusive. Additionally, most such tools rely on vision and audition as their medium for user communication. By their nature they are used in multi-task scenarios, so perceptual competition is the norm; the result often overwhelms, and routinely jeopardizes safety. Meanwhile, the tactile modality is often suggested as an underutilized alternative, but has other potential drawbacks (its own sensory load, nonperceptibility, annoyance).

In this research, we examine the use of Vibrotactile (VT) guidance cues to provide pedestrian cadence guidance, ultimately processed pre-attentively. We have previously reported sensorially optimal locations on the human body for processing pedestrian guidance cues (Karuei et al. 2011 [78]; and Chapter 3), and a validated algorithm that can measure realtime cadence well enough for interactive cadence guidance, with a commodity smartphone sensor (Karuei et al. 2014 [79];



**Figure 5.1:** PVG regulates a walker’s step frequency with subtle cues – to help him arrive at the bus stop at just the right time. Or, help a runner train at the right cadence, or a rehab patient exert the right effort.

and Chapter 4). Here, we demonstrate that given a periodic cue in a single-task scenario, walkers can adjust their step frequency to match it with minimal reported effort. In a final step reported elsewhere, we evaluate how this ability persists under varying types of sensory, physical and cognitive load.

## 5.2 Approach

Human walking is a repetitive movement whose rate is primarily characterized by the stride’s length and its frequency. Under normal circumstances, the walker (or runner) can control either one to achieve a desired speed: when one is constrained to increase or decrease, speed changes proportionally while the unconstrained parameter is relatively independent of this change [89].

We propose a simple way of guiding human cadence with VT cues: we map a desired walking frequency to the tempo of a PVG cue, and ask the pedestrian to match walking tempo to it. This guidance can subsequently be incorporated into feedback control to maintain or adjust the walker’s locomotion speed as desired or dictated by an application.

This means of communicating rate information fits well with known capabilities of the haptic channel, and could be helpful to pedestrians and athletes who need to efficiently manage the timing of repetitive movements (walking, running, rowing). Direct-mapped rather than abstract, PVG should require minimal learning, and have a lower steady-state impact on cognitive processing than symbolic cues [100, 156]. By freeing cognitive and attentional resources needed to attend

to ones' surroundings, they may improve safety directly and indirectly. Their simplicity may allow them to be combined with other methods of VT communication, for example to transmit higher-level activity information.

From a control perspective, PVG operates on a continuous spectrum; tempo and its inverse, the inter-cue interval, can be any positive real number. Continuous control affords many alternatives for control configuration and gain adjustment to achieve smooth, efficient regulation of cadence and speed. These include flexibility in judicious deployment of 'silence' breaks: long periods of VT stimuli should be avoided because too long or too many vibrations can become irritating to some users, and over-stimulation produces adaptation and loss of sensitivity [64].

### **5.2.1 Contributions**

Our quantitative contributions demonstrate empirically the potential effectiveness of PVG, with:

1. Data on the effect of tempo and repetition on walkers' ability to match stride to a VT cue, confirming a broad ability to do so given a comfortably realizable tempo; and
2. Evidence of walkers' ability to maintain cued frequency at least 30s after cue-off, important for avoiding cue adaptation.

This creates new opportunities for systems to help pedestrians control walking speed easily and accurately. We also share an experimental methodology with utility for future cadence-control development, and discuss implications for application design.

## **5.3 Related Work**

### **5.3.1 Perceptual Overload and Safety**

The critique of our dependency on eyes and ears for interacting with consumer electronics (*e.g.*, music players, GPS guidance tools, phones containing both) is well known. This reliance contributes to overload and inefficiency in visual and auditory perception [70, 101, 162], while the graphical and auditory interfaces them-

selves often fail when their target modalities are unavailable or inconvenient [167]. In other cases, in competing for required resources they undermine primary task performance [163]. Motor vehicle authorities increasingly acknowledge risks inherent in electronic device usage while driving, citing distracted driving due to texting or talking on the phone as directly responsible for upticks in collision statistics [127]. But pedestrians are equally at risk of attentional lapses [66, 71, 111], rendering them vulnerable to crossing streets more slowly while using a phone [66] and inattentive blindness [71].

The two obvious approaches to reducing visual and auditory, and ideally cognitive, load are to (a) limit the secondary task (*e.g.*, by not using a guidance tool), which is less desirable to the user; or (b) replace audiovisual cues, and their conscious processing, with VT cues that require little effort to interpret and ideally processed pre-attentively [11]. Examples include vibrations on the left or right side of the torso as turn direction indicators [163], alarms to warn of safety issues such as an unduly slow street-crossing or oncoming traffic or cues that influence walking speed to make travel more efficient and retain mental capacity for other situated tasks.

### 5.3.2 Spatial Vibrotactile Guidance

Spatial guidance systems typically provide event-driven cues not continuous control, but the relatively extensive efforts here are informative as to cue interpretability, attentional load and evaluation.

One class uses direct-mapping of vibratory stimulus to direction, *e.g.*, Ertan et al.'s system to guide blind users in unfamiliar indoors areas, with a 4-by-4 vest-embedded array which rendered a stop signal or cardinal direction [35]; or Bosman et al.'s use of tactors on both wrists to augment space perception in unimpaired wearers [11]. Tsukada & Yasumura achieved 8-direction guidance outdoors with a tactor belt [163], and Koslover et al. compared VT and skin-stretch signals with visual and auditory cues [86]. All of these systems have found users able to interpret direct-mapped spatial guidance with high accuracy.

In a different shared-display approach, Rukzio et al. coordinated a palmar VT phone display with a public 8-light display. The lights toggled on/off in a rotation,



and the phone vibrated when the direction on the public display matched the user's route direction [136]. Van Erp et al. investigated more abstracted VT navigation cues, displayed around the waist using four distance-coding schemes. Two related distance and tempo of stepping rhythm (faster tempo indicated shorter distance) and the others communicated departure, arrival, and intermediary phase by three distinct tempos of one rhythm [167]. Their VT system was a successful direction indicator but the distance indicators for walking needed improvement.

We envision a future system in which speed-control and direction cues are combined, with sufficient care taken to disambiguate them.

### 5.3.3 Periodic Guidance of Locomotion

Study of guiding *how fast* to walk is less common, yet pace guidance has obvious utility for mobile, Global Positioning System (GPS)-enabled navigation apps. These currently tend to assume an average walking speed applied to everyone to predict time-of-arrival and suggestions for departure time. In reality, people walk at different speeds. When arrival time is important (catching a bus or train, going to a meeting) walking speed may be as important as direction (Figure 5.1).

Walking is a repetitive task with a variable speed controlled as: walking speed = stride frequency  $\times$  stride length [89]. Individuals walk at a preferred frequency, which minimizes energy expenditure and depends on the person's body. A walker may adjust both stride frequency and length to control walking speed [29]. Laurent & Pailhous measured walker response to both metronomic cues and constraints on step length, and found that good pace control can be accomplished by constraining and controlling just one of the two parameters, due to their relative independence [89].

One auditory study found that metronome beeps can also guide walking cadence [29].

Ferber et al. used haptic cues delivered through foot pedals to maintain target intensity level on a stair-climber exercise machine while doing a mental task. Two methods embodied velocity-control ("on" when outside a target zone), and another gave metronomic VT cues at 2x the desired stepping rate. Results showed issues with perceptibility and signal understandability, and reported increases in

average parameters (velocity, power, and variance) rather than performance in step-level tempo matching. However, user reactions are relevant here: likeability and comprehensibility did not correspond to effectiveness at increasing effort, and the tempo-matching scheme was deemed hard to follow, and produced the greatest interference with a simultaneous task of any method tested.

In our own design we emphasized perceptibility, comprehensibility and low cognitive processing effort. Feet are not ideal for mobile cueing – sensitivity is low in the feet and degrades with movement body-wide as explained in Chapter 3 – so we proceeded with wrist-worn factors.

### 5.3.4 Controlling Step Rate

In the present work, we explore the use of continuous control on stepping frequency. The obvious alternative is discrete: a *bang-bang* (on-off) controller [5] that gives rate-control cues (“walk faster / slower”) when speed goes outside a specified band. This approach is simple to implement, and can be attempted with sensor sources subject to noise and dropouts, such as GPS.

However, when the control action is not well matched with system responsiveness (here, the walker’s variable response to the cue; or a runner’s heart-rate in reaction to a change in pace on a hilly route), the result oscillates between thresholds. The resulting discomfort can be experienced with many currently available heart-rate and GPS-based running speed regulation products. Oscillation is best mitigated by widening the control band, undermining precision. Guidance into multiple bands of desired velocity (for greater precision) does not improve stability, and can make the system harder to learn or conceptually understand.

Continuous control does need reliable data with accuracy, refresh and phase delays commensurate to control bandwidth requirements. Our implementation uses our Robust Realtime Algorithm for Cadence Estimation (RRACE) algorithm – which derives realtime step frequency estimates from a commodity smartphone accelerometer – with a phase delay, within 2 steps (Chapter 4).

## 5.4 Experiment

To ascertain the feasibility of low-level VT guidance of stride frequency, we needed to measure how well humans can synchronize their walking frequency with PVG, and how well they can maintain their walking frequency once the cue stops.

We hypothesized that

- H1** most people can follow the tempo of PVG with an accuracy  $\geq 90\%$ ;
- H2** tempos near an individual's natural walking frequency will be easier to follow (exhibiting lower cue divergence than extreme tempos);
- H3** error will be negative for fast tempos (walking cadence  $<$  cue) and positive for slow tempos (walking cadence  $>$  cue); and
- H4** magnitude of error will increase when the cue is turned off.

### 5.4.1 Apparatus and Context

Our setup consisted of a wrist-worn VT display, cadence sensing (four Android smartphones running a custom step-detection algorithm), and a control laptop as explained below. The laptop managed the procedures (Section 5.4.4) and sent commands to the VT display wirelessly while the phones constantly measured walking frequency.

To reduce measurement noise due to cornering, we collected data on a straight, wide, level walkway in a quiet residential area within a university campus. We found that 350 meters accommodated one minute of walking by the fastest-moving pilot participants.

#### **Client Side: VT Cues**

To deliver tactile cues to the participant's wrist, we used Tam et al.'s *Haptic Notifier* [156] (Figure 5.2). Relevant parts of this system are (i) an *Arduino Fio* microcontroller [151] with built-in *XBee socket*, (ii) *XBee series 2 radio* to communicate with the experimenter's laptop, (iii) three synchronized eccentric-mass tactors with a vibration frequency of  $\sim 190$  Hz (Section 3.3.1), and (iv) a lithium polymer battery.

To avoid communication delay between laptop and Arduino wrist controller, the Arduino logged the start / end of each trial and the time when haptic cues were turned off during the trial, according to its clock. These data were communicated to the laptop (server side) at the end of each trial. *Arduino* timestamps were converted to computer time in post-processing (Section 5.4.4).

We displayed two types of vibrations, all delivered at  $\sim 190$  Hz: the guidance cue (periodic vibrations, each 100 ms in duration, with an interval defined by the guidance tempo) and the stop signal (a single 5 s vibration, administered at the end of a trial). For example, for a guidance tempo of  $g = 2$  Hz, a trial's wrist-display vibrations would consist of: [0-20s]: 100 ms every 500 ms; [20-60s]: no vibrations; [60-65s]: 5 s vibration.



**Figure 5.2:** The *Haptic Notifier* (top) and the *Xbee* USB radio (bottom).

### **Server Side: the Experimenter's Laptop**

The experimenter ran the main control code on a laptop that acted as the server, responsible for: (a) Measuring the participant's fast and slow cadences and deriving the mid levels from those through the experimenter's key presses, which revealed start, end, and number of strides. (b) Logging synchronization times from the

wrist-worn Arduino, and the Android phones. (c) Reading the trial order from a pre-generated table. (d) Running the study step-by-step and send the commands such as “*start the trial*” to the Arduino. (e) Sending a request to the Arduino for logs at the end of each trial, receiving them, and saving them to a file.

#### **Cadence Measurement: RRACE**

We used four Android phones equipped with our custom RRACE algorithm for measuring users’ walking frequency (Chapter 4). We placed two phones in participants’ front pockets and the other two in a small backpack: while RRACE is especially robust to orientation and body placement, here we used locations previously shown to provide the highest accuracy. These phones logged the 3-D acceleration of the user’s thighs and torso and measured and recorded the user’s cadence every 200 milliseconds. Duplication provided robustness to issues such as the Android operating system terminating RRACE due to perceived CPU over-usage, or inadvertent button presses. We used the median of all active cadence estimations (to discard outlier measurements) to improve measurement accuracy.

### **5.4.2 Experiment Design**

Our experiment had two factors: guidance tempo (to assess response to divergence from natural step rate), and repetition (learning). Each trial consisted of 20 s with VT guidance and 40 s without.

An experiment session contained 16 regular trials (5 guidance rates  $\times$  3 repetitions + 1 dummy). Trials were put into out-and-back pairs for practical reasons; because 15 is an odd number, we added a dummy trial at the end (whose data were not used) to make sure the participant finished the experiment near the starting point.

**Factor 1 – Guidance Rate:** We coordinated five guidance rates to each individual’s own fastest and slowest walking frequencies (Section 5.4.3).

**Factor 2 – Repetition:** To ascertain learning (performance improvement as a result of exposure) we presented every guidance rate three times, arranged in three blocks, each consisting of the five rates in random order.

### 5.4.3 Computing Experimental Guidance Rates

In an initial calibration step, we measured participant  $i$ 's slowest and fastest cadences using RRACE, then matched that participant's two extreme custom guidance rates (cue tempos)  $g_i[1], g_i[5]$  to his/her slowest and fastest demonstrated cadences, respectively. We then distributed the middle rates evenly on a logarithmic scale; *i.e.*, the ratio of each two consecutive tempos ( $g_i[n+1]/g_i[n]$ ) is constant. Reference frequency  $f_r(t)$  was then set to one of  $g_i[1 - 5]$ .

### 5.4.4 Procedures

After introduction and consent, we asked the participant to walk at his/her slowest and fastest walking speeds. For each, we measured the time required for twenty strides ( $t_{20}$ ). Our experiment program computed the inter-step interval ( $\tau = t_{20} / 20$ ) and thence walking frequency ( $f = 1 / \tau$ ), to define this participant's  $g[1]$  and  $g[5]$  (slowest and fastest stride frequencies). We sent the tempos to the wrist-worn Arduino client, and synchronized the phones and Arduino clocks with the control laptop.

We next explained the task, the wrist display and the experiment format, then carried out a representative practice trial. Participants were explicitly instructed to try to (a) walk at the tempo of the cue, and (b) continue to walk at that same cadence after the cue stopped. This was repeated until the participant fully understood the protocol, and then the 15 actual trials (plus the dummy trial) were run. A session took about 45 minutes and we thanked each participant with 10 dollars.

**Pairing of Trials:** Participants walked away from the experimenter on a straight walkway for odd-numbered trials, stopped when they felt the sustained VT stop signal, then turned around. When they felt the new guidance cue they began walking again, proceeding until they again felt the stop signal (in some cases passing the experimenter). To conclude close to the experimenter, the experiment ended with a dummy trial number 16 with a random cue frequency; its data were not used.

### 5.4.5 Metrics

We described users' stride frequency with *cadence* ( $f$ ) and *cadence ratio* ( $\bar{f}$ ). Cadence is the walker's stride frequency, whereas cadence ratio is cadence divided by

*middle cadence*, defined as the geometric mean of that walker’s fastest ( $g_i[5]$ ) and slowest ( $g_i[1]$ ) stride frequencies, which was the guidance tempo  $g_i[3]$  in this study (Eq. 5.1). Cadence ratio was used to *normalize* participants’ cadences to their own middle cadence, to minimize offset and scale deviation due to individual variability in natural walking frequency and range.

$$\bar{f}_i(t) = \frac{f_i(t)}{g_i[3]} \quad (5.1)$$

We then measured departure from the guidance cue with *cadence error %*, defined as the difference between participant  $i$ ’s cadence ( $f_i$ ) and the tempo of the  $j$ ’th guidance signal (the tempo of the guidance signal at time  $t$ ), normalized to the latter and presented in percentage points:

$$e_i(t) = \frac{f_i(t) - g_i[j(t)]}{g_i[j(t)]} \times 100\% \quad (5.2)$$

#### 5.4.6 Analysis Technique

Cadence was measured every 200 milliseconds on all of the phones, each datapoint timestamped with the phone clock, and analyzed in (non-overlapping) two-second windows. We converted the timestamps of all the data from the phones to the computer time

We grouped the cadence measurements from all the phones at each window, removed outliers and used their median for subsequent analysis, and removed the first 4s where the participant is transitioning from a stationary position to natural walking. One datapoint/2s in 56s of usable trial yielded 28 datapoints/ trial.

We separated data into VT cues on/off; then used Generalized Linear Model (GLM) for statistical analysis of each region, with post-hoc pairwise comparisons with Bonferroni adjustment for multiple comparisons. To assess the effect of cue-off over time, we compared datapoints at different times in the cue-off region.

**Table 5.1:** Summary statistics of cadence error % by guidance condition for cue-on (top) and cue-off (bottom).

Cue On (18 s after the start of the trial)								
Guidance	mean	sd	median	min	max	skew	kurtosis	se
g1	-0.50	2.47	0.00	-6.61	3.78	-0.35	-0.54	0.40
g2	0.40	5.51	-0.04	-20.36	13.50	-0.13	4.32	0.84
g3	-0.64	2.51	-0.54	-7.58	7.10	-0.01	1.91	0.39
g4	-3.20	4.71	-1.04	-19.13	3.20	-1.35	1.71	0.73
g5	-7.70	7.42	-9.10	-21.58	2.40	-0.16	-1.48	1.11

Cue Off (58 s after the start of the trial)								
Guidance	mean	sd	median	min	max	skew	kurtosis	se
g1	6.11	6.07	6.50	-8.14	25.06	0.70	1.59	0.96
g2	3.43	5.26	2.74	-6.54	16.75	0.51	-0.36	0.83
g3	0.33	6.41	0.47	-24.06	10.56	-1.30	3.15	1.00
g4	-3.10	5.89	-1.47	-14.45	6.81	-0.47	-0.90	0.91
g5	-10.29	7.07	-10.98	-26.25	1.57	-0.33	-0.85	1.05

## 5.4.7 Results

### Data Summary

15 participants (9 male), aged 19 – 31 years ( $mean = 24.9$ ,  $SD = 3.6$ ), 152 – 196 cm tall ( $mean = 169.7$ ,  $SD = 11.2$ ), and weighing 39 – 90 kg ( $mean = 63.4$ ,  $SD = 14.2$ ) took part. 4, 2 and 9 participants respectively had none, <5 years, and >5 years of prior musical training.

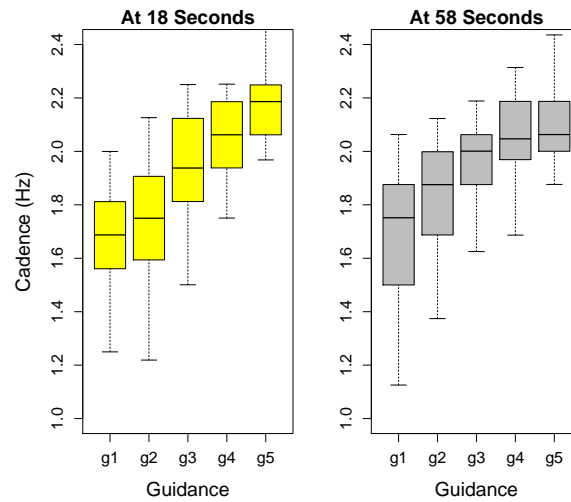
*Stride frequency* increases with cue tempo ( $g_1 \dots g_5$ ) even 38 seconds after turning off the cue, *i.e.*, at  $t = 58$  s (Figure 5.3). The fastest VT cue shows less success at making users walk faster ( $g_5$  and  $g_4$  are too close in Figures 5.3 and 5.4).

*Cadence error %* demonstrates how well people are following the VT cues: positive (or negative) error % means the participant’s cadence is faster (or slower) than the cue tempo. Figure 5.5 shows that when the cue is on, users closely follow the cue tempo (average error < 4%) except for the fastest (average error -7.7%). When we turn off the VT cue, step rate diverges more from cue tempo and (unsurprisingly) tends towards the middle stride rate.

*Individual post-cue divergence* is best seen by viewing data from a single participant (second repetition) as a set of time series. Figures 5.6-5.7 are scatter plots with a smooth curve fitted by the Locally Weighted Regression (LOESS)



method [24]; Participant 4 was chosen randomly from 12 of the 15 participants showing a similar response pattern. Consistently with the aggregate views, 20 seconds into the trial when the cue stops, cadence error starts to grow, although for some tempos, it quickly plateaus. For slower guidance cues ( $g_1$  and  $g_2$ ) cadence error is generally positive, and negative for faster cues ( $g_4$  and  $g_5$ ).

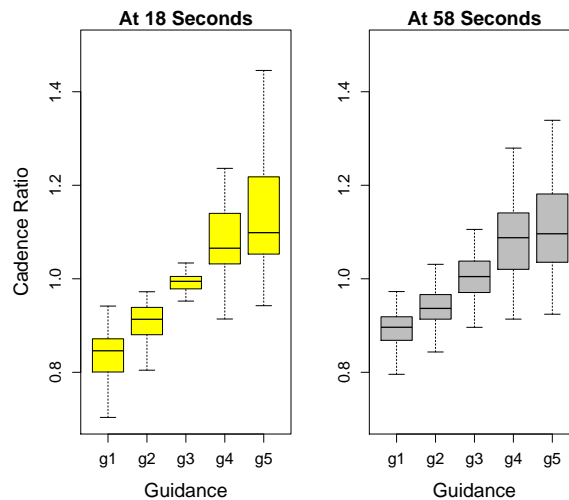


**Figure 5.3:** Cadence by guidance rate (average of all participants and all repetitions), when cue is on (left/yellow, at 18s); and off (right/gray, at 58s). Despite inter-individual variability, the cue-linked cadence increase is clear in both cases. Guidance rates are individual-specific and thus cannot be shown.

### Statistical Analysis

We separately analyzed guidance and non-guidance periods, to investigate whether cadence error % is significantly different (a) under different guidance conditions when the cue is on and off, (b) at different points in time since the start of the trial when the cue is on, and (c) at different points in time after the cue is stopped (see Table 5.1).

*VT Cue On:* The statistical analysis of Generalized Linear Model of the data showed that for cue-on, guidance rate and time from trial start have a significant effect on cadence error % ( $p < 0.05$ ). Pairwise comparisons show that each two of the guidance tempos differ significantly from each other. These factors also interact with each other ( $p < 0.05$ ), with a simple explanation: under slower guidance



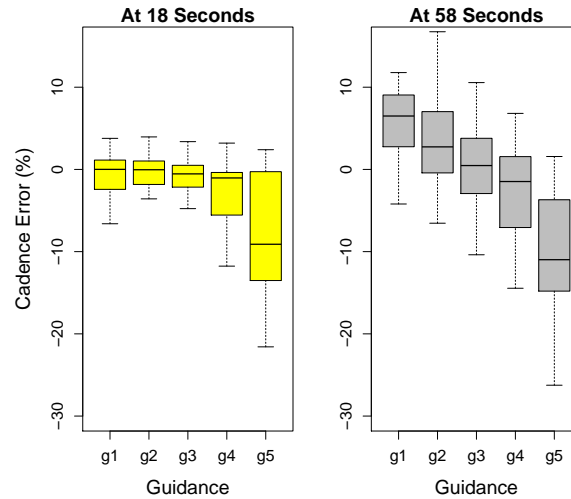
**Figure 5.4:** Cadence ratio by guidance rate, when cue is on (left, at 18s) and off (right, at 58s). Cadences normalized to the participant’s middle tempo), in contrast to non-normalized cadences of Figure 5.3, show less individual variance and the difference between the 5 levels is clearer.

tempos, walkers start with a positive error that shrinks as the cue continues, and under faster tempos participants start with a negative error that then shrinks.

In the temporal response, the first measurement after the 4s transition period removed for this analysis (Section 5.4.6) was significantly different from the rest of the measurements during the cue-on region, but there is no significant differences between subsequent 4s windows in the guidance period. This indicates that participants aligned their walking rate with the cue tempo early on, attained stability by 4s, then maintained it thereafter.

*VT Cue Off:* Similarly to cue-on, when the guidance cue is off, guidance rate and time into trial (or since cue-off) significantly impact cadence error % ( $p < 0.05$ ). They also interact with each other in the cue-off region, with an explanation similar to above. Pairwise comparisons show that each two of the guidance tempos are significantly different from each other.

Temporally, two of the first measurements after stopping the cue were significantly different from two other times near the end. This means that the error increases in amount when the cue stops but the change in error is so slow that there is little difference except for points sufficiently far apart in time.

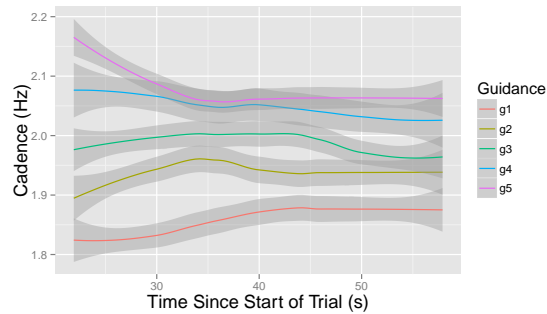


**Figure 5.5:** Cadence error % by guidance rate, when cue is on (left, at 18s) and off (right, at 58 seconds). At the end of the cue-on phase (left), the smallest error is seen in the lower three levels,  $g_1$ ,  $g_2$ , and  $g_3$  (means:  $-0.5\%$ ,  $0.4\%$ ,  $-0.6\%$  respectively) and the largest with  $g_5$  ( $-7.7\%$ ). After the cue stops, absolute value of error grows faster for  $g_1$  and  $g_2$  (absolute value of means increase 5.6 and 3.0 respectively) than all other rates.

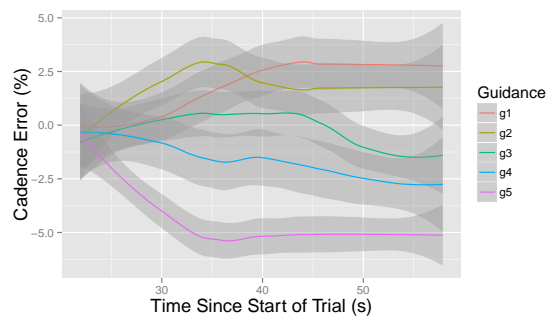
### 5.4.8 Discussion

Our experimental results confirm that periodic VT cues can easily affect pedestrian’s walking frequency, when consciously followed (less than 5% divergence in four out of five cue rates and less than 10% during the fastest) ( $H1$  accepted). Our results showed that for tempos distributed across an individual’s full walking range, divergence from cued tempos near and lower than individual’s natural walking frequency is lower ( $H2$  rejected). Error increases when the cue is turned off ( $H4$  accepted), but this increase happened at a subtle rate within the 40s window we observed.

When a user tries to synchronize steps with a cue, the direction of error and its upper bound are generally predictable: positive when the cue is faster than walker’s typical cadence and negative when slower ( $H3$  accepted). A benefit of this predictability is the possibility of mitigating overall error in a Closed-loop Control system by anticipating the worst case scenario and adjusting the cue to compensate, *i.e.*, by applying a model of the walker’s response to this low-level stimuli.



**Figure 5.6:** Scatter plot of P4’s *cadence* during trials 6-10 by guidance rate with smooth curve fitted by the LOESS method. Bands represent the confidence interval of the LOESS method. From guidance cue off (20s) to trial end (60s), cadence converges toward the walker’s typical cadence.



**Figure 5.7:** Scatter plot of P4’s *cadence error %* during trials 6-10 by guidance rate (colour coded) with smooth curve fitted by the LOESS method. From guidance cue off (20s) to trial end (60s), cadence error tends to grow (further from zero) at least initially, then stabilizes in some cases.

## 5.5 Conclusions and Future Work

In this chapter we proposed Periodic Vibrotactile Guidance (PVG), for regulating pedestrian stride frequency. An exemplar application is guiding a commuter toward the closest bus stop at the optimal walking speed, not sweating when there is time for a stroll nor missing the bus when a slightly faster pace is sufficient. Other applications for PVG include athletic training (a long-distance or sprint runner or rower, seeking to maintain a step-level pace) and rehabilitation (displaying desired step frequency to a patient instructed to achieve a given effort or mobility level, and no more).

Our results confirm that taction, and in particular stimuli applied through a wearable to the wrist, is a viable choice for such applications. It is not used in larger task of locomotion, and does not compete for perceptual or motor resources that other tasks (listening, reading, even texting on a mobile device) might; simple to learn, it is likely to be cognitively lightweight as well.

Whether audible or tactile, periodic guidance has a potential for more stable, comfortable cadence regulation than the common alternative, bang-bang velocity control, although this premise remains to be tested. Specifically, its continuity allows for deployment in close-loop control systems – most simply a Proportional-Integral-Derivative (PID) controller – that can further improve the user’s performance by adjusting the cue based on current state, previous error and future predictions, with gains adjusted to the user’s needs and physiological responsiveness. An interesting next step will be to explore the control parameter customization needed for different task scenarios and individual differences.

Our experiment tested individuals’ ability to match stride frequency with a VT cue displayed to the wrist. Most (13/15) could synchronize at 95% accuracy across their full range of walking speed, with a 5-10% lag behind cues faster than their natural cadence, and 5% lead ahead for slower cues, without significant training. In day-to-day applications such as pedestrian guidance this error ratio will be negligible relative to other factors: a 5% error for a 15 minute walk is equal to 45 s, and is predictable enough for a planning algorithm to compensate for it. In applications that require more accuracy such as training athletes, users’ focus and effort could improve accuracy. Ideally, we would like users to “lock the buzz” to a particular point in their walk cycle to achieve maximum accuracy and stability; however, without data on the phase of walking cycle we cannot be sure if that was achieved by some users or not.

Walkers maintained their stride frequency within a manageable bound after cue-off; divergence was slow enough to contemplate use of (at least) 30s ‘silence’ breaks between cued periods, important for avoiding irritation and adaptation. The actual length of silence breaks can be further optimized by a Closed-loop Control algorithm.

### **5.5.1 Future Work**

As we proceed stepwise to a fully viable control approach, the most immediate next step after verifying conscious cue-matching ability is to examine subconscious step-matching to VT cues. This is an essential component of a viable control approach for users unlikely or unable to fully concentrate on step rate for any length of time.

Set up as a dual-task scenario, important cases to consider will be distracting auditory, visual and cognitive tasks with qualities similar to those that we do while walking and exercising (listening to music or podcasts, talking on the phone, navigating a map, or perhaps even regarding our surroundings. Workload imposed by the PVG system on any of these tasks, and of them on step-matching performance, are of keen interest.

Finally, we anticipate that using PVG in a simple closed-loop format will be key to its applicability. Many variables remain to be investigated on this topic: *e.g.*, whether modifying vibration intensity in proportion to target tempo divergence will improve performance, and the many possible means of incorporating silence periods to mitigate adaptation and improve acceptability.

## **5.6 Acknowledgment**

This work was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) and the GRAND NCE. User data were collected under University of British Columbia's Research Ethics Board approval H01-80470.

## Chapter 6

# Periodic Vibrotactile Guidance of Human Cadence, Performance during Auditory Multitasking

*The degree of slowness is directionally proportional to the intensity of memory.*

*The degree of speed is directionally proportional to the intensity of forgetting.*

— Milan Kundera, *Slowness*

In this chapter we<sup>1</sup> evaluate the viability of a haptic cueing approach for guiding pedestrian walking cadence with regards to workload, walker’s performance, and interference with auditory tasks. We previously demonstrated that pedestrians can synchronize and maintain walking frequency with vibrotactile pulses delivered on the back of the wrist from a wristband. Here, we examine walker’s guidability in the face of realistic auditory multitasking scenarios (listening to podcasts, or music of varying rhythmicity). We measure workload and walkers’ performance under three guidance rates and four auditory tasks. Our results suggest that while auditory tasks – in particular, those with verbal content – do undermine cadence matching performance, stepping synchrony is generally achieved with  $\geq 90\%$

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<sup>1</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.

accuracy within 10 seconds. Vibrotactile guidance does thereby successfully affect walkers' speed. Perceived guidance-related workload is statistically significant but not related to cueing frequency; future work will assess its practical significance.

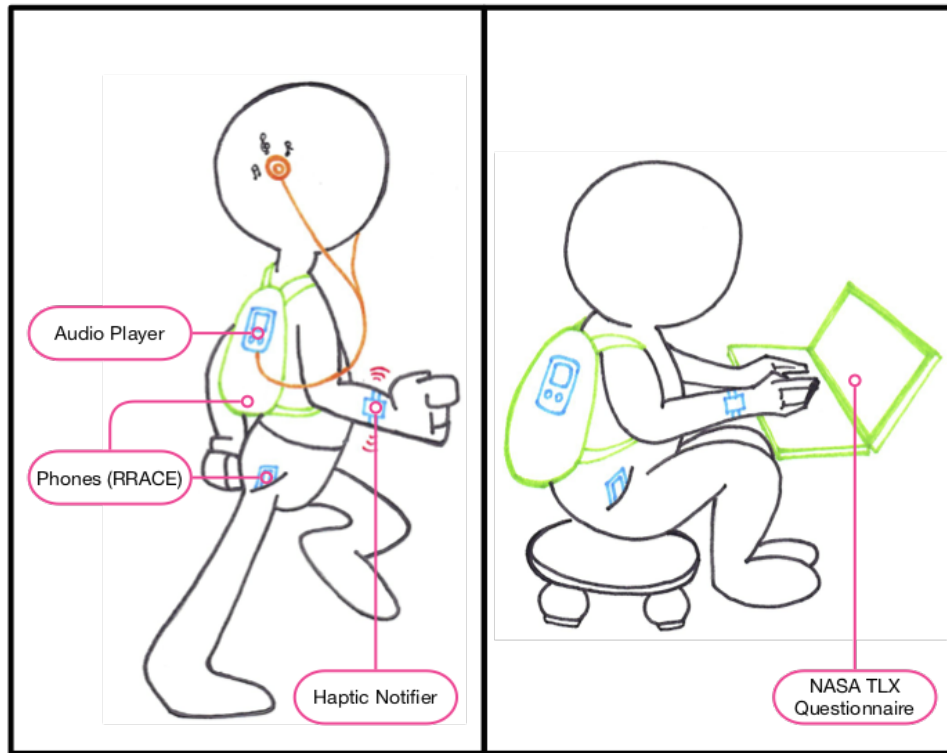
## 6.1 Introduction

Multitasking has become one of the main themes of our lives; society encourages it, our ambitious lifestyles demand it, and technology facilitates it. Sadly, productivity does not always improve; instead, the competition for mental resources imposed by tasks conducted in parallel may slow us down or cause mistakes. When multitasking is unavoidable, technology needs to mitigate negative impact – *e.g.*, by simplifying a task, improving its timing, or diverting the required processing to a less-used cognitive resource. A good example is the auditory step-by-step directions that have become the norm for GPS navigation devices; augmenting the graphical interface with auditory signals enables drivers to keep their eyes on the road, and breaking the directions into small steps makes guidance signals easier to digest.

Guidance (*e.g.*, for time management, navigation, and finding nearby services) is by definition multitasking: the guidance happens in parallel to a primary task (*e.g.*, coordinating a meeting, walking to a destination). Replacing or augmenting the visual interface with an auditory one may reduce some negative effects (*e.g.*, looking at the device instead of the road while walking or driving) but may also create new usability challenges. For example, audition can be as occupied as vision (listening tasks), while environmental noise can further interfere with perception. The tactile modality is often suggested as an underutilized alternative.

Haptic cues, most conveniently implemented as Vibrotactile (VT) stimuli, have the potential to apply less attentional load than visual and auditory cues, and conflict less with situational awareness and other listening tasks. The larger goal of this project is to establish the degree to which this can be exploited in pedestrian guidance. In earlier steps, we identified sensorially optimal locations on the human body for processing pedestrian guidance cues (Karuei et al. 2011 [78]; and Chapter 3), and a validated algorithm that can measure realtime cadence well enough for interactive cadence guidance, with a commodity smartphone sensor





**Figure 6.1:** Experiment setup. Left: during a trial, the participant carries four smartphones equipped with RRACE algorithm for cadence measurement (two in front pockets and two in backpack); another smartphone (audio player) is attached to the backpack with its screen facing out for the experimenter to choose and play the audio tracks. The haptic notifier is worn on the participant’s wrist. Right: the participant answers the NASA-TLX questionnaire on a laptop after each trial pair.

(Karuei et al. 2014 [79]; and Chapter 4). We then determined the range and accuracy with which walkers are able to synchronize their stepping cadence with VT cues (Karuei and MacLean 2014 [76]; and Chapter 5), by asking the pedestrian to walk to the cue beat, and to continue with this cadence after a cue stopped.

This brought us to the focus of the present chapter: how well can walkers follow these cues during realistic auditory multitasking; and what is the magnitude of the workload that VT cues impose on them?

## 6.2 Approach

Human walking, like many other movements (running, swimming, rowing), is repetitive and its speed is defined by stride frequency (cadence) and length. Typically, a walker controls both parameters, unconsciously, to achieve a desired speed; however, when one parameter (stride length or frequency) is constrained to increase/decrease – within the walker’s ability – speed also changes proportionally [89]. We explore the potential to exploit this property of walking in three sequential steps.

**1. *Periodic Vibrotactile Guidance (PVG):*** Our guidance scheme is driven by periodic tactile cues, which render a desired frequency to the walker through the skin as a stepping target. This means of communicating rate information fits well with known capabilities of the haptic channel and may be helpful to pedestrians and athletes who want to closely but efficiently manage the timing of repetitive movements. Direct-mapped, PVG should require minimal learning and have a lower steady-state impact on cognitive processing than symbolic cues [68, 100, 156]. Periodic cues are also simple enough to be combined with other haptic communication such as navigational or higher-level activity information.

**2. *Evaluating PVG and Workload:*** In the study reported here, we found that most pedestrians can continue to synchronize their cadence with the VT cue tempo, even in the face of a variety of types of auditory tasks. As a result, PVG successfully affected the walking speed of pedestrians in the cued direction. Workload measured under various combinations of auditory stimuli and VT guidance further showed that workload due to tactile guidance is noticeable, but the cue frequency does not significantly change its amount. We found that workload increase due to auditory input was small compared to that from PVG, and had only a small impact on the user’s ability to follow stepping cues. On average, users required about 8 seconds to achieve a steady cadence from a stationary start.

**3. *Control of PVG:*** Ultimately, we plan to incorporate PVG into feedback control to maintain or adjust the walker’s locomotion speed according to an application’s changing specifications. Tempo ( $f$ ) and its inverse – the cue interval ( $T = 1/f$ ) – can be any positive real number which provides PVG a continuous spectrum to

operate on. This characteristic affords many linear and non-linear feedback control configurations to achieve fast, smooth, efficient, and/or error-free regulation of cadence and speed. While this manipulation is beyond our present scope, it has informed the design of the present study.

### **6.2.1 Contributions**

The present evaluation provides:

1. Data on the effect of PVG rate and auditory task on cadence, stride length, and walking speed.
2. Data on the effect of PVG and auditory task on workload during walking.
3. Analysis of walkers' ability to follow PVG cues during auditory multitasking, comparing guidance rates and auditory tasks in terms of performance and workload.
4. Experimental methodology for measuring walking performance and workload during auditory multitasking, for re-use in exploring other workload-reducing stratagems.
5. Recommendations on how to incorporate PVG so as to minimize its workload-related impact.

These findings will inform improved pedestrian guidance systems, which by reducing guidance-related mental effort can be helpful without compromising safety. Our experimental methodology can be re-used in similar settings to better understand motor control and cognitive functions and their relationship to auditory and tactile stimuli, particularly for development of tactile and/or guidance applications.

## **6.3 Related Work**

### **6.3.1 Vibrotactile Guidance**

As previously outlined in greater detail (Section 5.3.1), a secondary task that uses audiovisual channels – *e.g.*, via a Global Positioning System (GPS) device – competes for resources required for an aurally or visually demanding primary task (*e.g.*,

driving or walking). This contributes to overload and inefficiency in visual and auditory perception [70, 101, 162], undermines primary task performance [163], and can thereby endanger safety and cause substantial stress.

The two obvious approaches to reducing visual and auditory, and ideally cognitive, load are (a) limiting the secondary task (which the user may find unacceptable), and (b) replacing audiovisual cues with a lower-effort alternative.

Guidance of movement in *space* is one activity where the tactile modality has exhibited promise as a replacement or augmentation for visual and auditory channels. Examples demonstrating its unloaded guidance potential include Ertan et al.'s embedded tactor array for rendering cardinal directions and stop signals [35], Bosman et al.'s wrist mounted tactors for guidance in indoor places [11], and Tsukada and Yasumura's tactor belt capable of communicating the four cardinal and four intermediate directions through eight tactors around the waist [163]; for a full review, see Section 2.1.6.

Temporal (or spatiotemporal) guidance has the additional challenge of time-variant dynamics. Maruyama et al.'s *P-Tour* [104] and ten Hagen et al.'s Dynamic Tour Guide (DTG) [159] are examples of spatiotemporal guidance which schedule visiting of tourist attractions based on the user's location. Both of these use graphical interfaces; this presents a potential sensory conflict with problematic results. Alternatively, the Haptic Notification System (HANS) by Tam et al. is an example of temporal guidance for time management during oral presentations, delivering interrupt-based cues to the presenter and the session chair at certain points in time during the presentation [156]. While this application was found to present minimal additional sensory load, by its nature it required cognitive processing to make use of the cues which in turn required practice and training, and thus is not directly comparable to our aims in pedestrian support.

We envision a system where time management, speed, and direction cues are combined in a navigation tool to help users achieve their goals with safety and efficiency.

### 6.3.2 Guidance of Human Locomotion

Walking is a repetitive task with a variable speed controlled by cadence (or stride frequency) and stride length [89] as shown in Equation 6.1.

$$\text{walking speed} = \text{cadence} \times \text{stride length} \quad (6.1)$$

When unconstrained, we tend to walk at a speed most comfortable for us; generally one that minimizes energy expenditure per distance [130]. Increasing or decreasing walking speed is achieved by changing stride frequency and stride length [83]. It is possible to control walking speed through constraining stride length [89, 119, 170], stride frequency [89], speed, or both [10]. As these are all obviously related, one might expect to see a compensatory effect from stride length (or frequency) when altering stride frequency (or length). However, Laurent and Pailhous showed that these parameters are relatively independent, while each one is instead strongly correlated with *speed* [89] – hence, an opportunity to control walking speed by constraining and controlling stride length *or* stride frequency.

Stride length guidance has generally been achieved by visual cues such as tape markers [89, 119, 170]; stride frequency by auditory cues such as metronomic beats [10, 29, 89]. Haptically, Ferber et al. tried different methods for guiding workout speed on a stair climber. Their metronomic approach (taps on the user’s feet at double the rate of the desired cadence) did not give promising results [37]. In Chapter 5 we evaluated the use of periodic vibrotactile cues to guide human cadence, and ultimately speed. In our design, we emphasized perceptibility, comprehensibility, and low cognitive processing effort. Feet are not ideal for mobile cueing (sensitivity is low in the feet and degrades with movement body-wide – Chapter 3), so we used wrist-worn tactors [156]. We found a basic ability to follow cues, as well as its limit: participants fell behind fast VT cues and walked faster than slow cues, relative to their typical cadence (Chapter 5). That is, rather than exactly matching the cued tempo, the cues *appeared to exert upward or downward pressure* on actual walking tempo.

### 6.3.3 Temporal Guidance and Auditory Task

Multiple Resource Theory (MRT) posits that the interference between two tasks depends on how much they share stages (cognitive vs response), sensory modality (auditory vs visual), codes (visual vs spatial), and channels (focal vs ambient) [171]. In this regard, VT guidance (periodic or non-periodic) has little to no interference with a pedestrian's vision. However, PVG and any auditory task (*e.g.*, listening to music or podcasts or conversing) could interfere with each other in two areas: non-visual sensory perception and motor control.

Mammals (and humans in particular) may be subject to three temporal scales and/or mechanisms: *the circadian clock* involved in metabolic rhythms; *an interval timer*, flexible, cognitively controlled, and active at seconds to minutes; and a *millisecond clock* for speech, music, motor control [17]. Ideally, PVG will engage the millisecond clock and impact motor control, eventually reducing mental workload via downgraded reliance on the “cognitively controlled” interval clock in daily tasks (*e.g.*, deciding when to start or end a task based on temporal constraints). As a result, the sensory perception of both the vibrotactile cues and auditory tasks that are time-sensitive, such as listening to music, would share the millisecond clock. On the other hand, movement timing depends on basal ganglia (involved in interval timing) and cerebellum (millisecond timing). The latter is also heavily involved in rhythm synchronization and music perception [176].

This suggests that listening to music, especially the rhythmic variety, will interfere with/be most affected by PVG. To test this, we used auditory tasks with obvious and subtle rhythms, or with verbal content.

### 6.3.4 Performance and Workload

Methods employed to evaluate mobile and handheld systems include qualitative (interviews and observations) and quantitative (*e.g.*, error rate and timing of events with the help of video recording [123]). The active component of mobile use has been considered via heart rate and deviation from preferred walking speed [84], and cognitive workload [84, 123].

Rubio et al. group tools for evaluating physical and mental *workload* into performance-based, physiological, and subjective measure categories [135]. They

note the frequent use of subjective procedures due to ease of implementation, non-intrusiveness, and sensitivity to operator load. Of the subjective workload measures we employ – NASA Task Load Index (NASA-TLX), Subjective Workload Assessment Technique (SWAT), and Workload Profile – the first [65] has seen the most use in VT guidance research. Two of many research examples are Pielot & Boll’s use of NASA-TLX to measure workload of their tactile navigation system “Wayfinder” and compare it with a commercial pedestrian navigation system [122]; and Hoggan et al’s investigation of perception of mobile multi-actuator tactile displays that use rhythm and location [70].

In the present research, our primary concern is to observe performance and workload as a result of our experimental conditions. Our quantitative performance metrics includes *cadence*, *cadence error %* (i.e., divergence from the guidance cue), *stride length*, and *speed* and we used the full NASA-TLX to measure perceived workload, which includes *mental demand*, *physical demand*, *temporal demand*, *performance*, *effort*, *frustration*, and *total workload*. We did not collect other qualitative or subjective metrics at this stage (e.g., regarding participant preferences) to keep experimental sessions to a manageable length and because they will be more relevant in a setting where participants use PVG over longer periods of time.

### **6.3.5 Measuring Cadence**

*Accurately and usably* guiding cadence will require Closed-loop Control (CLC), and concomitant accurate realtime measurement of actual step-rate. With only open-loop control (no system access to resulting rate), the designer has little alternative to constant-level, ongoing cue output regardless of need, and this is bound to cause user irritation and stimulus adaptation. While discussion of possible CLC algorithms are beyond our present scope, the availability of adequate cadence measurement technology is enabling to our larger aims as well as necessary to collect the data reported here.

Cadence can be measured using many different technologies, from traditional pedometers equipped with mechanical or piezoelectric sensors to accelerometer-based instruments [43, 106, 174] (see Chapter 4 for a full review of these and

several other methods). In order to be used in a guidance system, a cadence measurement should be: (a) sufficiently accurate, (b) realtime, (c) robust to placement, orientation, and user differences, and (d) portable. We previously presented RRACE (Robust Realtime Algorithm for Cadence Estimation), which meets these requirements through a frequency-based approach, in Chapter 4. RRACE measures momentary cadence via frequency-domain analysis of accelerometer signals available in smartphones. We used RRACE in our experiment (Section 6.4.5); however, its development and cadence measurement in general are not key parts of the present evaluation.

## 6.4 Experiment

We conducted an experiment to assess the effect of auditory task on a user’s performance, and the amount of workload PVG imposes on the user in conditions with and without several key types of auditory tasks. We hypothesized that:

- H1** PVG will influence the user’s cadence, stride length, and walking speed in the cued direction.
- H2** Auditory task will interfere – variously – with the effect of PVG on cadence, stride length, and walking speed, with greatest impact for highly rhythmic music.
- H3** Users will be able to synchronize step cadence with the guidance cue within 5-10 seconds.
- H4** Presence of PVG will increase workload, with greatest impact for faster cues.
- H5** Auditory task will add to workload during walking, with the effect greatest for a verbal task (*e.g.*, listening to a podcast).

### 6.4.1 Experiment Design

We used a within-subject repeated-measures design with two factors: *guidance tempo* and *auditory task*. Each trial lasted 25 s, and was part of a two-trial, out-/return repeated pair; *i.e.*, the subject executed a given condition once in each direction, finishing the return trial close to the starting point. An experiment session



contained 24 trials: two instances of 3 *guidance tempos*  $\times$  4 *auditory task* conditions.

### 6.4.2 Guidance Conditions

We used three guidance conditions: *fast*, *slow*, and *no guidance*. Because each participant has a personal natural cadence, in an initial calibration step we measured the participant's typical cadence by timing ten steps and measuring the average step interval, then matched the fast and slow guidance rates to 1.15 and  $1/1.15$  times his/her typical cadence, respectively. This ratio value was decided based on the average range of participants' cadences, as informed by our previous study (Chapter 5). There, we set the fastest and slowest tempos to each participant's fastest and slowest cadence and distributed the other three rates between them; but found that variance in how participants chose their fastest and slowest rates (narrow vs broad range) reduced our data's consistency. Here, we used the same fast/slow ratio (*i.e.*,  $1.15^2$ ) for all subjects.

Our current focus was workload and performance, and the effect on them of auditory tasks. We therefore tested two rather than the five guidance rates of Chapter 5, allowing us to include a range of auditory conditions for a reasonable session length.

In Chapter 5 we used a baseline guided tempo near the participant's natural cadence, which turned out to be uninformative. Here we replaced this with a no-guidance baseline that would permit comparison with guided conditions for cadence, cadence error, overall movement speed, and subjective workload.

### 6.4.3 Auditory Tasks

We tested four auditory task conditions: *podcast*, *techno*, *classical*, *silence* (Table 6.1).

*Podcast* examined the effect of verbal auditory tasks on participants' performance. Another option, an actual scripted phone conversation administered by a confederate, was infeasible due to low controllability.

We sampled the diverse space of music, a key pedestrian diversion, by varying rhythmic emphasis, on the premise that this will generate higher PVG interference

**Table 6.1:** Auditory task conditions used in evaluation.

Type	Task	Comments
Verbal	<i>Podcast</i>	Engaging (but obscure) segment to fully hold attention: “What Caused the Sabre-Tooth Tiger Extinction”, produced and broadcasted by CBC’s “As It Happens” [19]. All participants confirmed its novelty.
High Rhythm	<i>Techno</i>	Non-vocal techno song called “Supa-Dupa-Fly” with a typical techno-trance structure, and a simple and distinctive rhythm. We produced several samples with varying tempos.
Low Rhythm	<i>Classical</i>	Johann Sebastian Bach’s “Air on G String” – consistent melodic elements devoid of strong or repetitive rhythm. One version (conventional tempo) was used.
Baseline	<i>Silence</i>	No auditory stimuli

than melodic variation. Factor levels were high (*techno*) and low (*classical*).

*Choice of auditory rate:* Techno music slower than a pedestrian’s typical cadence would sound strange, whereas a beat faster than the fast VT cues would reinforce, rather than conflict with, the VT cue – undermining experiment objectives.

We resolved this by choosing a single auditory tempo near the geometric mean of the participant’s typical cadence and the fast cue ( $f_{techno} = \sqrt{1.15} \times f_{typical}$ ). Modifying the music on the fly to match participants’ unique cadence and guidance rates was impractical, so we prepared 14 versions in advance and chose the best-fit at run time. The average of humans’ typical cadence is 2 Hz (120 BPM), so we created a 120 BPM base version, plus eight faster and five slower versions. Each rate was 1.036 (=  $1.15^{1/4}$ ) times faster/slower than the adjacent ones, ranging from 1.679 Hz (100.8 BPM) to 2.645 Hz (158.7 BPM).

#### **6.4.4 Metrics**

The following metrics were computed for each sample, and an aggregate value compiled for each trial.

##### **Cadence**

Stride frequency was sampled at 1 s intervals using RRACE (Chapter 4) running on four Android phones.

##### **Cadence Error %**

The participant's measured error (divergence from guidance rate) divided by guidance rate at each sample. The sign of the error indicated whether the participant was behind or ahead of the tempo.

##### **Cadence Ratio**

Measured cadence divided by walker's natural cadence, at each sample. Normalization was performed due to large individual differences in natural cadence.

##### **Speed**

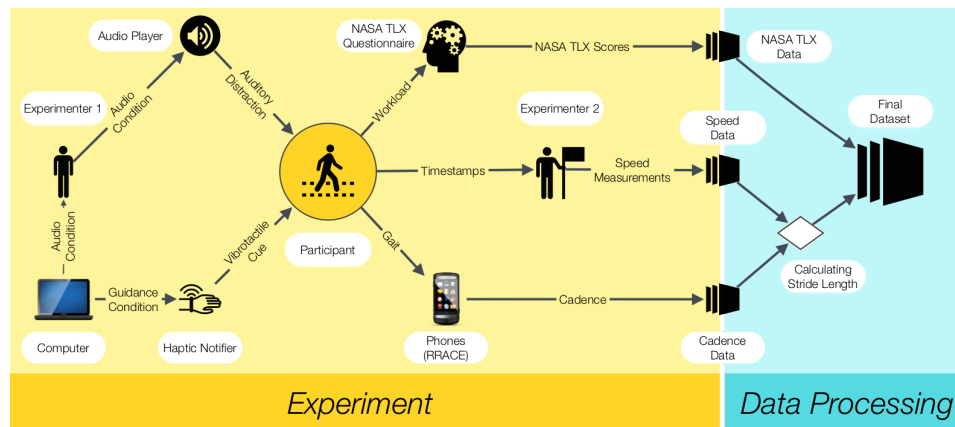
The participant's average walking speed during a single trial. We placed two coloured flags, one about 2 m after the starting point and another  $\sim 17$  m from the first. An experimenter (E2) timed participants as they passed the flags, going away and coming back. Speed was post-computed as distance between the flags divided by elapsed time.

##### **Speed Ratio**

Measured speed during a single trial divided by that participant's speed during the baseline condition (silence with no guidance). This parameter allows combination of speed measurements from all the participants.

## Subjective Workload

Participants reported workload using two-part NASA-TLX questionnaires after each trial pair (going away, coming back). In Part 1, the participant rates six subscales addressing *mental demand*, *physical demand*, *temporal demand*, *performance*, *effort*, and *frustration* on a single page, in a 100-point range in 5-point steps (20 grades). In Part 2, the participant adds weights to these subscales via pair comparisons (e.g., *physical demand* versus *frustration*); as 15 questions, one per page. Each NASA-TLX questionnaire took about 2 minutes to complete. We used the total workload index and the six subscales in our analysis.

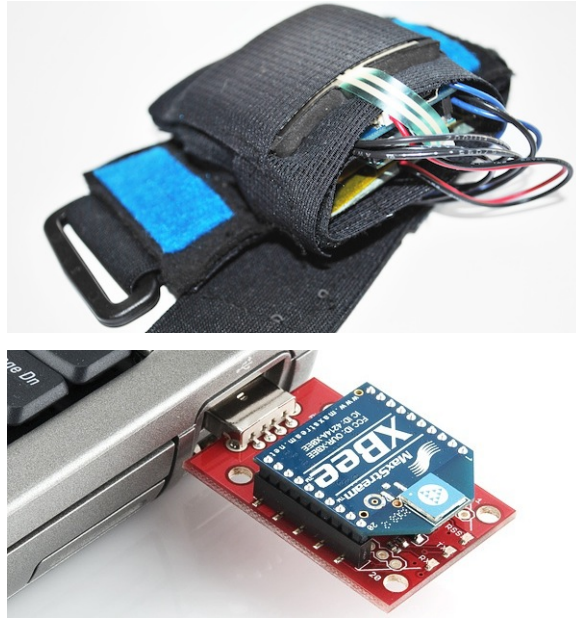


**Figure 6.2:** Data flow, throughout the experiment and after the experiment during data processing.

### 6.4.5 Apparatus and Context

Our setup consisted of a wrist-worn VT display, cadence sensing (four Android smartphones running a custom step-detection algorithm), a control laptop, an Android phone to play audio files, a stopwatch, and a questionnaire laptop.

Experiment information flow is shown in Figure 6.2 (yellow area). Two experimenters carried out the protocol. The control laptop managed study conditions by informing Experimenter 1 (E1) which pre-chosen audio track should be selected for each trial, and sending commands wirelessly to the VT display. The phones constantly measured walking frequency. E2 administered the NASA-TLX question-



**Figure 6.3:** The *Haptic Notifier* (top) and the *Xbee* USB radio (bottom).

naire after each trial and timed participants for speed measurement.

### VT Cues – Android Wrist Display

To deliver tactile cues to the participant’s wrist, we used Tam et al.’s *Haptic Notifier* [156] (Figure 6.3). We used three types of vibrations, as detailed in Table 6.3.

**Table 6.2:** Elements of Android wrist display [156].

<i>Part</i>	<i>Quant</i>
<i>Arduino Fio</i> microcontroller [151] with <i>XBee</i> socket	×1
<i>XBee</i> series 2 radio to communicate with experimenter laptop	×1
synchronized eccentric-mass <i>tactors</i> (~ 190 Hz – Chapter 3)	×3
lithium polymer battery	×1

The laptop and the Arduino were synchronized via timestamps at session start, then operated independently during trials to avoid communication delays. The Arduino logged the trial start / end, then communicated to the laptop at trial completion (Section 6.4.6).

**Table 6.3:** Vibrations used in study ( $\sim 190$  Hz). *T* (turn) and *S* (stop) use similar vibrations, *T* ends an odd trial and begins an even trial, *S* ends an even trial (and the trial pair).

<i>Cue</i>	<i>Occurrence</i>	<i>Description</i>	<i>Dur</i>
C: count to 3	start of odd trial	(0.5 s vibration +0.5 s silence) $\times 2$ +1 s vibration	3 s
G: guidance	during trial	100 ms vibration, interval defined by guidance tempo	$1/f$
T: turn	end (start) of odd (even) trial	5 s of constant vibration	5 s
S: stop	end of even trial	5 s of constant vibration	5 s

### Overall Experiment Control: Base Laptop

The main control code ran on a server laptop, responsible for: (a) Measuring the participant’s fast and slow cadences, and deriving mid levels through the experimenter’s keypad entries which marked start, end, and number of strides. (b) Logging synchronization times from the wrist-worn Arduino, and the Android phones. (c) Reading the trial order from a pre-generated table. (d) Running the study step-by-step and send the commands such as “*start the trial*” to the Arduino. (e) Sending a request to the Arduino for logs at the end of each trial, receiving them, and saving them to a file. This laptop remained in a stationary location while the participant walked out/back, within continuous wireless range.

### Smartphones – RRACE Cadence Measurement

For redundancy, we used four RRACE-equipped Android phones to measure walking frequency (Chapter 4). We placed two phones in participants’ front pockets and the other two in a small backpack: while RRACE is robust to orientation and body placement, here we used locations previously shown to provide the highest accuracy. These phones logged the 3-D acceleration of the user’s thighs and torso and measured and recorded the user’s cadence every 200 milliseconds. Duplication provided robustness to issues such as the Android operating system terminating RRACE due to perceived CPU over-usage, or inadvertent button presses. We used the median of all active cadence estimations (to discard outlier measurements) to

improve measurement accuracy.

A fifth smartphone, used to play audio files, was mounted on the shoulder bag with its display accessible to E1 (Figure 6.1).

#### 6.4.6 Procedures

We recruited participants through university mailing lists and posters around the campus. The experiment took about 60 minutes and participants were compensated \$15. The actual experiment had the following steps, where P indicates the Participant and E1, E2 the experimenters.

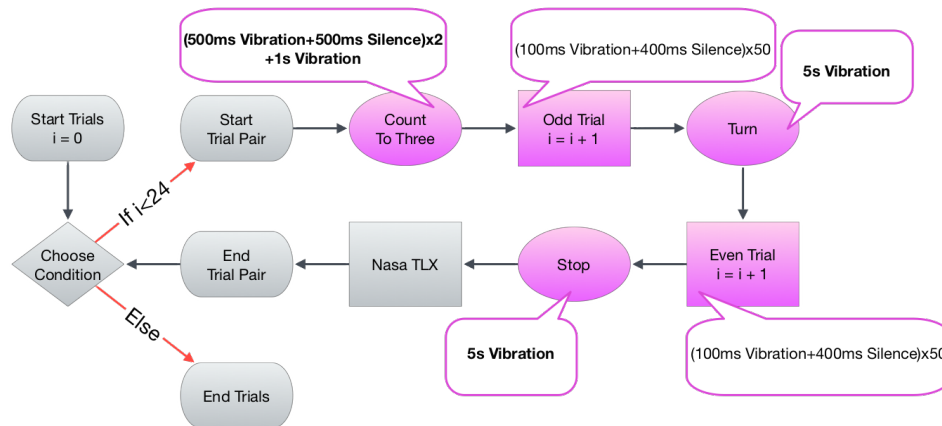
##### 1. Calibration and Instruction:

- *Introduction and consent*
- *Cadence baseline:* While P walked at his/her typical walking speed, E1 measured time required for twenty strides ( $t_{20}$ ) and computed average inter-step interval ( $\tau$ ) and walking frequency ( $f = 1/\tau$ ). Guidance tempos were set to  $1.15\times$  faster and slower than the typical cadence, and sent to the wrist-worn Arduino client.
- *Synchronization:* Arduino and smartphone clocks were synchronized with the control laptop.
- *Instructions:* E1 explained task, wrist display and trial format, then instructed P to execute fast and slow practice trials. P was instructed to try to walk at the cue tempo, and requested to practice until in full understanding of protocol.
- *Equipage:* E1 placed two smartphones in the participant's front pockets, and three in or on a small shoulder bag.

##### 2. Trials, Run in Pairs:

The 24 trials were performed in 12 pairs; paired trials shared conditions (auditory task and guidance tempo) but had different walking directions (odd numbered trial: away from the starting point, even numbered trial: towards the starting point).

- *Preparation:* P stood at starting point near E1, who then started audio (except in the silent mode).



**Figure 6.4:** Flowchart of the experiment. Beginning in upper left, a single loop is one trial pair, to be repeated 12 times (trial number  $i$  increments twice in each loop). Purple denotes presence of VT cues (except in no-guidance conditions), and rectangles data collection. The 100 ms vibration during trials is the same across all *guided* trials but the vibration interval (and the silence) during trials is defined by the tempo of the guidance cue; here, for a tempo of 2 Hz, the vibration interval is 500 ms and therefore, the silence is 400 ms.

- *Odd trials:* Following a VT count to three, P paced away from E1 for 25s.
- *Turning around:* When notified by a continuous 5s vibration, P stopped and turned around.
- *Even trials:* Without pause, P stepped towards E1 for 25s.
- *End of trial pair:* P received a continuous 5s vibration and stopped. E1 stopped audio (if not silent mode).
- *NASA-TLX questionnaire:* P sat down and completed the NASA-TLX questionnaire on a laptop administered by E2 while E1 wirelessly downloaded the start and end timestamps from the haptic notifier to the computer.

### 6.4.7 Data Preparation

Cadence was measured every 200ms on all of the phones, and each datapoint timestamped with the phone clock. After converting phone timestamps to computer time, data were analyzed at 1 s intervals. Figure 6.2 illustrates data flow throughout the experiment and during data processing.



- *Cadence*: We grouped cadence measurements from all four data-collection phones at each timestep (*i.e.*, four observations at  $t$  seconds after the start of trial where  $t \in N$  and  $t \leq 25$ ) and used their median (to guard against outliers). In subsequent analysis, we removed the first four seconds of each trial, where the participant is transitioning from a stationary position to natural walking. This procedure produced one datapoint / s in 20s of usable trial, yielding 21 datapoints / trial (*i.e.*,  $t \in \{5, 6, \dots, 25\}$ ).
- *Cadence error*: We computed *cadence error %* from cadence measures and guidance frequency for that sample.
- *Speed and stride length*: We added manually-measured speed (Section 6.4.4) to cadence data, and computed stride length as speed divided by cadence (Equation 6.1).

#### 6.4.8 Analysis Technique

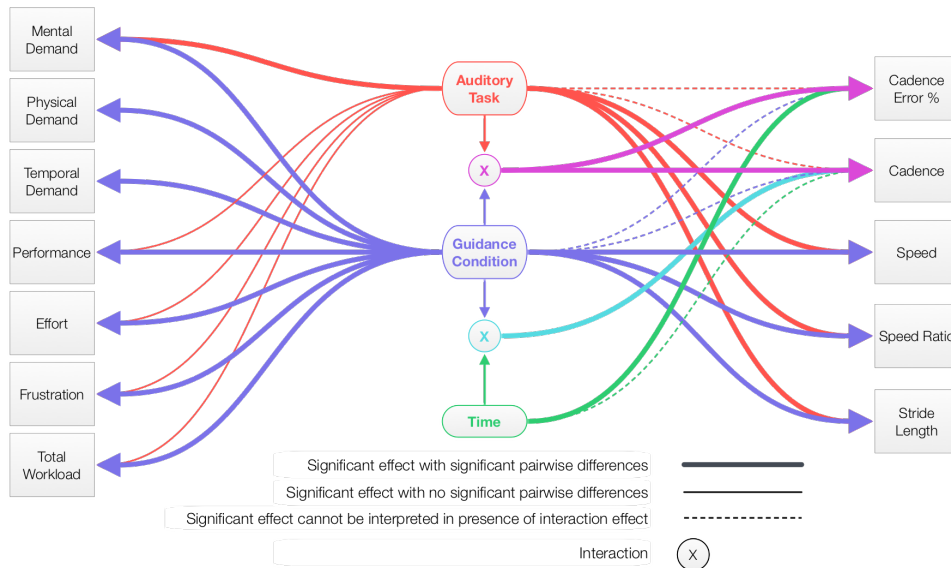
We used Generalized Linear Models (GLM) for statistical analysis of performance and workload data, followed by a Tukey post-hoc test for multiple pairwise comparisons.

When there was no interaction effect between factors, we conducted pairwise comparisons on every significant main effect. Otherwise, we analyzed the interaction in terms of simple effects (Rutherford <sup>2</sup>): we divided the dataset by one factor ( $n$  subsets for  $n$  levels of the factor), and analyzed the statistical significance of the other factor. We then conducted pairwise comparisons of its levels on each of those subsets separately and repeated this with the two factors switched.

For example, for physical demand, guidance emerged as the only significant main effect. Thus, we only compared guidance conditions: *fast vs slow* guidance, *slow vs no guidance*, and *no vs fast*. In contrast, *cadence error %* had three significant main effects (guidance, auditory task, and time) and an interaction between guidance and auditory task. In this case, we first used pairwise comparison of time because it did not interact with other factors; second, we split the dataset by guidance condition into two subsets, and conducted pairwise comparisons of four

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<sup>2</sup> [138] Section 3.2.1, pg. 55; Section 9.3, pg. 169.



**Figure 6.5:** All statistical effects visualized with  $p = 0.05$  as significance level. The three factors (auditory task, guidance tempo, and time) and their interactions (auditory task  $\times$  guidance tempo and guidance tempo  $\times$  time) are colour coded in red, violet, green, pink, and cyan respectively. We omitted the interaction between auditory task and time because it was never significant. Significant main effects and interactions are shown with three types of arrows: (a) significant effects that cannot be interpreted because of presence of interaction, (b) significant effects with no pairwise difference between any two of their levels, and (c) significant effects with significant difference between some of their levels are shown with dashed lines, thin solid lines, and thick solid lines, respectively.

auditory tasks on each of the two subsets; and third, we split the dataset by auditory task into four subsets and compared *fast* with *slow* guidance for each.

## 6.5 Results

In this experiment 24 participants (11 female), aged 19-58 ( $mean = 25.96$ ,  $SD = 10.2$ ), 157 – 190 cm tall ( $mean = 171.3$ ,  $SD = 9.5$ ), and weighing 43.5 – 100 kg ( $mean = 66.59$ ,  $SD = 14.5$ ) took part. 11, 7, and 6 participants respectively had none,  $< 5$  years, and  $\geq 5$  years of prior musical training. 14, 9, and 1 participants respectively had none,  $< 5$  years, and  $\geq 5$  years of prior performing arts training including dance, ballet, and theatre.

### 6.5.1 Presentation of Results

This study employed five guidance and seven workload metrics, with an analysis based on GLM and Tukey pairwise comparisons. To visualize this complexity, we focus on important common patterns and exceptions. Omnibus analysis results are available in Appendix D.4, and Figure 6.5 displays significant main and interaction effects.

*Number of pairwise comparisons:* Because *cadence error %* is only meaningful when there is a guidance cue, the *no guidance* condition is omitted when analyzing *cadence error %* but presented for other metrics. Therefore, *cadence error %* has only the *fast-slow* comparison for guidance conditions. All other metrics have three guidance conditions and three pairwise comparisons: *fast-slow*, *slow-no guidance*, and *no guidance-fast*. Auditory conditions are the same across all metrics: four conditions and six pairwise comparisons. Because the number of pairwise comparisons for time factor was significantly higher, we only report the time after which there is no significant difference between any two times. In summary: for a factor with  $n$  levels, there will be  $n(n-1)/2$  pairwise comparisons ( $n$  choices for the first condition and  $n-1$  choice for the second condition divided by two to account for symmetry). Tukey's test subsequently compensates for the increase in probability of making a type I error caused by multiple comparisons.

### 6.5.2 Cadence Error %

PVG *suggests* a stride frequency to users; it is up to users to follow this frequency. Analyzing *cadence error %* shows us how successfully users of our system can follow the cue. Indeed, guidance condition affects *cadence error %* regardless of all other factors (Figure 6.6). *Cadence error %* is always negative under *fast* guidance (mean =  $-18.9\%$ , *i.e.*, users fall behind the cue tempo) and its magnitude is larger than error under *slow* guidance (mean =  $-12.7\%$ ). It is largely skewed (magnitude of median is much smaller than the mean) by poor performance of six users. *Cadence error %* is also affected by auditory task, but this effect is small relative to that of guidance condition. *Podcast-techno* (mean =  $-18.2\%$  vs  $-12.5\%$ ), *classical-silence* (mean =  $-19.2\%$  vs  $-13.3\%$ ), and *techno-classical* are significantly different regardless of guidance condition; the results of pairwise

comparisons in each guidance subset are shown in Table 6.4.

**Table 6.4:** Pairwise comparisons of *cadence error %* of auditory task levels per each guidance condition. P, T, C, and S are *podcast*, *techno*, *classical*, and *silence* respectively. Auditory tasks are sorted within each guidance subset by mean of *cadence error %* in the last column (Order) from left to right; all means are negative with the largest magnitude to the left.

Guidance Subset	P-S	P-C	P-T	T-C	T-S	C-S	Order
Slow	No	Yes	Yes	Yes	Yes	Yes	CPST
Fast	Yes	No	Yes	Yes	No	Yes	PCTS

*Cadence error %* only changes significantly during the first seven seconds after start of trial.

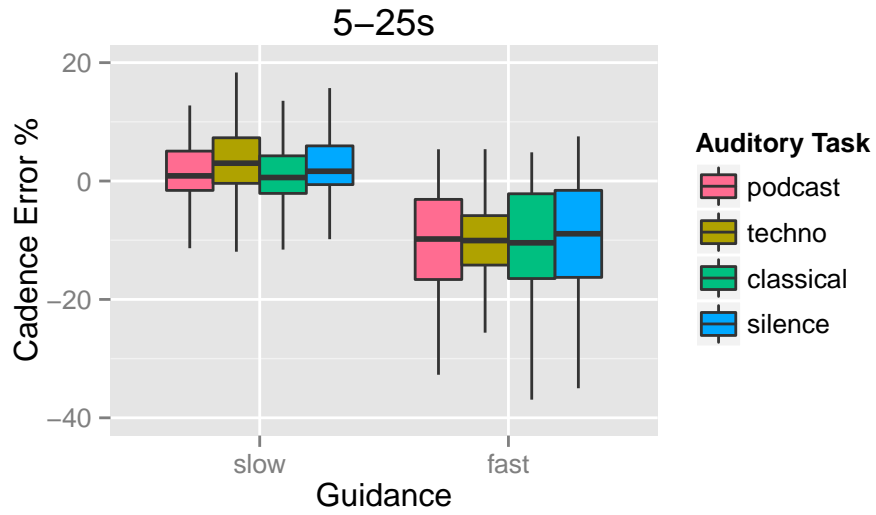
### 6.5.3 Cadence

Can PVG affect participants' cadence despite the error and in presence of auditory task? Cadence values do track guidance cue rate (mean = 1.79Hz, 1.70Hz, 1.46 Hz for *fast*, *no*, and *slow* guidance respectively; Figure 6.7). All guidance conditions are significantly different from each other in terms of cadence regardless of auditory task, with the exception of *techno* music (no significance for *no-fast* guidance).

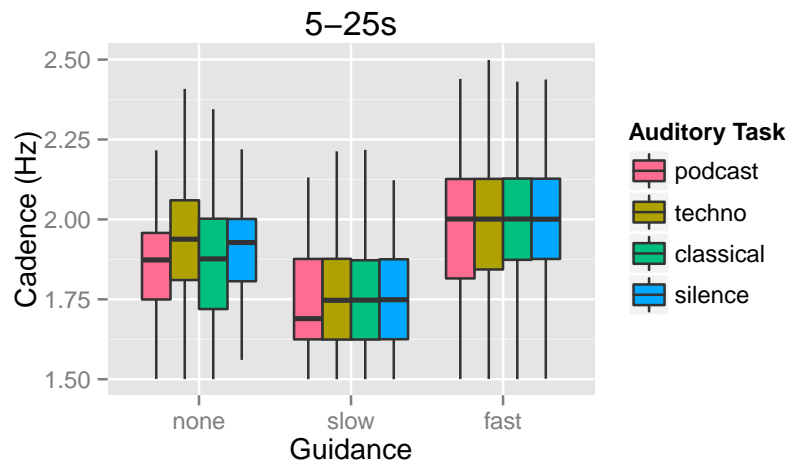
*Podcast-techno* (mean = 1.59 Hz vs 1.72 Hz), *classical-silence* (mean = 1.56 Hz vs 1.69 Hz), and *techno-classical*, are significantly different from each other regardless of guidance condition; Table 6.5 shows comparison results in each guidance subset. Cadence stops changing significantly at 7, 8, and 10 seconds after the start of trial under *slow*, *fast*, and *no guidance* condition respectively.

**Table 6.5:** Pairwise comparisons of cadence of auditory task levels per each guidance condition. Auditory tasks are sorted within each guidance subset by mean of cadence in the last column (Order) from left to right.

Guidance Subset	P-S	P-C	P-T	T-C	T-S	C-S	Order
None	Yes	No	Yes	Yes	Yes	Yes	PCST
Slow	No	Yes	Yes	Yes	Yes	Yes	CPST
Fast	Yes	No	Yes	Yes	No	Yes	PCTS



**Figure 6.6:** *Cadence error %* per guidance condition and auditory task. Guidance and auditory task (main effects) as well as their interaction are significant.



**Figure 6.7:** *Cadence* per guidance condition and auditory task. Guidance and auditory task (main effects) as well as their interaction are significant.

#### 6.5.4 Speed, Stride length, and Speed Ratio

Is speed and/or speed ratio affected by PVG in presence of auditory task? Does stride length play a role? Walking speed under *slow* guidance, mean = 1.20 m/s, is significantly different from *no* (1.38 m/s) and *fast* guidance (1.44 m/s), regardless of auditory task. Speed under *podcast* (1.29 m/s) is significantly different from *techno* (1.38 m/s) and *silence* (1.36 m/s) and different between *techno-classical* (1.33 m/s), regardless of guidance condition. Stride length completely follows the pattern of speed. Speed ratio also follows speed with one exception: *no guidance* is also different from *fast* guidance regardless of auditory task (Figure 6.8).

#### 6.5.5 Workload

Patterns in NASA-TLX results are relatively simpler than cadence (Figure 6.5). *No guidance* differs from both *slow* and *fast* guidance across all seven NASA-TLX factors including total workload index, regardless of auditory task. In every factor of the seven, *fast* guidance scores highest (most workload) and *no guidance* the lowest.

Auditory task is a significant main effect for five NASA-TLX factors (mental demand, performance, effort, frustration, and total workload) but the only significant difference between two auditory tasks is for mental demand and is between *podcast* and every other auditory task regardless of guidance condition.

### 6.6 Discussion

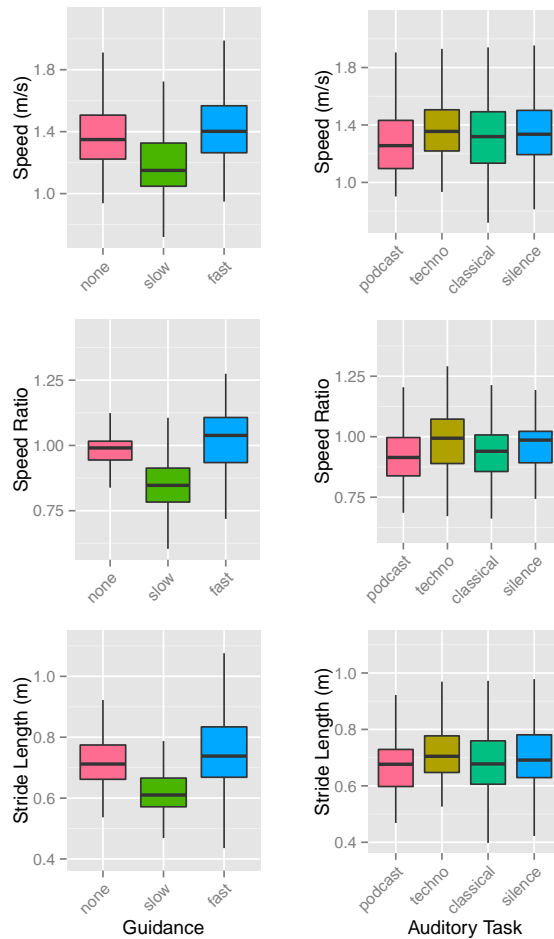
#### 6.6.1 Guidance Cue

*HI: PVG will influence the user's cadence, stride length, and walking speed in the cued direction. All parts accepted.*

Our results from this experiment confirm those of our previous experiment (Chapter 5) in showing that most people can synchronize their stride frequency with VT cues either very (here, 9/24 have median absolute error < 5%<sup>3</sup>) or reasonably well (13/24: < 10%). The two studies differ in that here, for consistency we

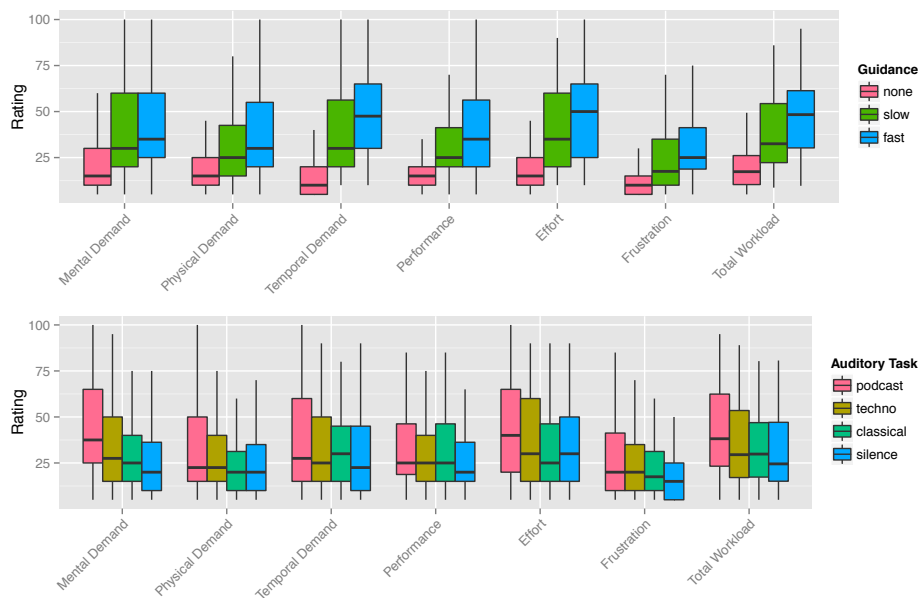
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<sup>3</sup>8 s after the cue starts to the end of trial.



**Figure 6.8:** Speed (top), speed ratio (middle), and stride length (bottom) per guidance condition (left) and auditory task (right). Guidance and auditory task (main effects) are significant for all the three metrics.

defined min/max walking tempos, resulting in more extreme (and more difficult) tempos to follow than when participants set their own; and, we added sensory and cognitive competition in the form of auditory tasks. As before, participants generally walk faster than *slow* guidance which produces a very small error and walk slower than *fast* guidance with a moderately larger error. When participants did not receive any cue they were inconsistent in their own typical walking frequency, suggesting that the VT cue is useful even at the user's typical cadence. Our analysis



**Figure 6.9:** NASA-TLX results colour-coded by guidance condition (top) and auditory task (bottom).

showed that PVG successfully affected participants’ cadence and speed regardless of auditory task.

Stride length is obviously also an important component of speed. Our analysis showed that *slow* VT cues cause participants to take significantly smaller strides relative to their typical stride length, but under *fast* guidance, stride length remains at a typical level. This could explain why *fast* cues impact speed relatively less effectively than *slow* cues despite their effect on stride frequency. However, the effect of *fast* VT cues is still sufficiently large to increase speed ratio (the participant’s speed relative to his/her own baseline speed). We employed VT cues 15% faster and 15% slower than participants’ typical cadences and achieved 20% change in speed from slowest to fastest.

### 6.6.2 Effect of Auditory Task on Performance

*H2: Auditory task will interfere – variously – with the effect of PVG on cadence, stride length, and walking speed, with greatest impact for highly rhythmic music. First part accepted.*



Although the auditory tasks seemed to affect cadence, analysis of each auditory task level revealed a strong interaction with guidance condition. It seems that highly rhythmic music that is faster in tempo than a user's typical cadence may indeed reinforce the fast guidance by encouraging the user to walk faster. In contrast, listening to a *podcast* or *classical* music seems to slow down the user; in the case of a faster than typical guidance cue, it slightly reduces the impact of guidance. However, the effect of auditory task on other metrics such as speed and stride length is independent of guidance condition. Participants take smaller strides and walk more slowly when listening to a *podcast*, and take longer strides and walk faster under *techno* music. However, this difference in stride length and speed (7% in the case of speed, speed ratio, and stride length) is much smaller than the difference caused by the guidance cue (20-21%, from *slow* to *fast*).

### 6.6.3 The User's Response Time

*H3: Users will be able to synchronize step cadence with the guidance cue within 5–10s seconds. Accepted.*

Elapsed time since the start of the trial also significantly affected cadence error but the result was predicted: because participants started each trial from a stationary mode, cadence increased during the first few seconds (7-8s) and cadence error decreased. After that, cadence and cadence error did not change significantly.

Furthermore, by comparing that response time with the time it takes participants to start walking from a stationary position until getting a steady cadence under *no guidance* (roughly 10s), we can conclude PVG can get pedestrians up to speed significantly faster than a single notification would (*e.g.*, the start signal at the beginning of *no guidance* trials).

### 6.6.4 Effect of Guidance on Workload

*H4: Presence of PVG will increase workload, with greatest impact for faster cues. First part accepted, second rejected.*

PVG adds to the total perceived workload measured by NASA-TLX by increasing all six basis scores. However, *fast* and *slow* guidance rates were not associated with significant changes in any workload score. This suggests that the workload

caused by PVG is real but it is likely that the tempo of the recurring VT cue does not change the amount of workload (Figure 6.9).

### 6.6.5 Effect of Auditory Task on Workload

*H5: Auditory task will add to the workload during walking, with the effect greatest for a verbal task (e.g., listening to a podcast). Partially accepted.*

Auditory task has no effect on physical and temporal demand and very little to no effect on the other NASA-TLX scores including total workload. While listening to *podcast* seems to cause the most workload for participants, it is only significantly different from silence and the two musical tasks in its effect on mental demand. This suggests that the additional workload of auditory tasks similar to these are small compared to the workload caused by guidance (Figure 6.9).

### 6.6.6 Interpreting Subjective Workload Measures

NASA-TLX scores in our experiment cannot be used to precisely compare auditory and guidance workload (or to scores reported in other works) because of differences in how we encouraged participants to focus on the two tasks throughout the protocol (not just at a NASA-TLX assessment time). It is possible that the participants were using different calibrations in their assessment of the two tasks.

In addition, there is a discretization aspect of NASA-TLX reports in that if participants noticed a difference between two conditions at all (e.g., *slow/no guidance*) they would give a nonzero score simply for noticing it, even if the impact was extremely minor.

As noted by Hart, these subjective workload measurements are relative (e.g., *fast vs no guidance* or *listening to podcast vs silence*) and lack a “redline” indicator when workload is *too high* [65]. Statistical significance of their difference does not necessarily translate to practical significance. If *fast* guidance caused less workload than the *techno* auditory task, then if we consider listening to *techno* music to be a low-workload task, we can easily argue that *fast* guidance is also a low-workload task. However, having a workload that is higher than listening to *techno* cannot be used for the opposite argument.

## 6.7 Conclusion

In this chapter we presented a workload evaluation of periodic vibrotactile guidance. PVG is a system that uses cadence synchronization to guide a pedestrian's walking speed without reliance on audiovisual channels, and it was important to evaluate the degree to which this may indeed be helpful. We also presented a framework for evaluating pedestrian cadence assistance in outdoor settings, with experimental control over cue rates, guidance mode, and a diversity of auditory tasks, and suitably accurate measurement of resultant step rate. We measured performance metrics such as cadence, cadence error (*i.e.*, divergence from the desired cadence), stride length, and walking speed in addition to perceived workload measured through computerized NASA-TLX questionnaires.

We have proposed a series of successively more difficult goals addressed in this evaluation. The first is simply that most people can follow stepping cues to a useful accuracy (90% and above) in a reasonable amount of time (under 10 seconds). The results reported here support this, and are also consistent with a non-workload previous study (Chapter 5).

Next, we confirmed an impact on speed. We knew it was possible that under increasing cue frequency, participants might take shorter strides. This would reduce the effect of faster cues, cancel them out, or even reduce walking speed. We observed, however, that under faster guidance stride length remained the same but cadence increased and *both* were lower under slower cues and thus the resultant speed was guided in the right direction.

There will of course be a limit in this, and now we have also identified some evidence for where it might lie, in the imperfect and somewhat skewed responses we did see. It is reasonable to anticipate that when we increase cadence even further, participants may stop increasing step rate altogether, and/or their stride length could start to decline and eventually impact their speed management.

For PVG to really be useful, it needs some degree of robustness against auditory task interference, along with the baseline visual load involved in walking: processing auditory streams is something that pedestrians using this assistance will likely wish to do at the same time. PVG depends on millisecond timing system of the brain [17] and affects motor control, and does not depend on speech or complex

cognitive tasks. Further, rhythmic music might directly mask or compete with a tactile cue. We therefore anticipated that PVG performance would be most damaged by music and particularly rhythmic music, and less by a verbal task such as listening to a conversation (a podcast in this experiment). Surprisingly, listening to a podcast interfered most severely with guided walking. The auditory task's effect does not have a practical significance when compared with the workload effect of guidance. However, our study only addressed tasks that involved processing of imposed auditory stimuli. It is possible that the workload caused by speech generation – *e.g.*, during a conversation or in recall of memories – could cause considerably more workload.

Finally, while we cannot yet rate PVG workload in terms of its real world implications, it is evidently noticeable at minimum, and requires further investigation.

## 6.8 Future Work

There are two immediate major directions in which this work supports expansion: a more in-depth understanding about inherent PVG merits, flaws, and limitations; and design of integrated, practical guidance systems that incorporate the findings of this work and others that come ahead.

The perceived increment in workload due to vibrotactile guidance is statistically significant. Future work needs to assess the practical significance of this strain, which our methods could only register as perceptible relative to an absence of guidance. With simple variations in experiment design, we can also generate more comprehensive characterization data. For example, by increasing trial length we can study learning effects and long term impact, and by considering generative auditory tasks such as conversation or questions and answers over a phone call our data will extend into other realistic scenarios. These were not possible within the scope of a single study but are important. It may also be productive to consider other cognitive impact metrics besides workload via the NASA-TLX; for example, measuring attention, perhaps via the Stroop test [102]. Administering Stroop during walking could be a challenge, and care must be taken not to introduce a confound. We have considered assessing a Stroop test immediately after a trial based on the fact that the effect of guidance (and/or auditory tasks) on attention does not

vanish right away.

We are also interested in extending our findings to the design of closed-loop PVG systems that consider additional contextual information such as time of events, geolocation of the user, traffic, and interruptions. Perhaps most interestingly, we see Closed-loop Control as a means of mitigating the small but important strain we have found that PVG can impose on the walker. A practical VT guidance system with context as well as highly resolved cadence and speed presents several potential advantages. It can choose a rate that is optimal based on spatiotemporal constraints of the user (*e.g.*, distance to destination and time of events) and task difficulty (*e.g.*, slope of the street and weather condition). It can selectively turn off the cue for a period of time, to both reduce workload and prevent physical stimulus adaptation [64]. Finally, now that we know that a fast cue does not necessarily cause more cognitive workload than a slow cue, a control system knowledgeable of the user's larger context could lower workload when most needed – *e.g.*, at a street crossing, the system could turn off the cue and allow the user to go off course, then adjust the guidance rate upward to compensate. Designing such a system will be challenging but possible by pairing increasingly available context-aware technology and algorithms with a close observation of pedestrian needs, and cognitive, sensory, and physical abilities.

## **6.9 Acknowledgment**

This work was funded by the Natural Sciences and Engineering Research Council of Canada and the GRAND NCE. User data were collected under University of British Columbia's Research Ethics Board #H01-80470.

## Chapter 7

# Conclusion

*All our knowledge begins with the senses,  
proceeds then to the understanding, and ends with reason.*

*There is nothing higher than reason.*

— Immanuel Kant, Critique of Pure Reason

In this dissertation we<sup>1</sup> introduced periodic guidance which employs the tempo of periodic cues in a fine-grained control setting. We provided evidence that showed tactile sensation is a better fit than vision and audition for most applications of periodic guidance. On the other hand, among different types of tactile displays, vibrotactile displays were more readily available and generally more powerful than others, therefore, we used vibrotactile displays and called our system Periodic Vibrotactile Guidance (PVG). We used PVG for guidance of human walking and studied the user's susceptibility to periodic cues, PVG's workload, and the effect of auditory multitasking on it. In this chapter we explain the primary contributions of this work, reflect on the research approach taken, and suggest some directions for future work.

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<sup>1</sup>For a list of contributors and their level of involvement please refer to the Preface on page iv.

## 7.1 Primary Research Contributions

### 7.1.1 Study of Sensitivity to Vibrations in Mobile Contexts

In the first phase of this work (Chapter 3), we wanted to find the best locations on the human body for placement of vibrotactile displays, especially for mobile applications including our own PVG system. A considerable amount of research has been done on sensitivity to vibrations [70, 73, 90] and the effect of movement on tactile sensitivity [3, 22, 23, 124]. On one hand, the research on relative vibrotactile sensitivity by site did not examine (a) movement and its interference with other factors and (b) expectations about stimulus locus; on the other hand, the research on effect of movement on sensitivity did not compare relative vibrotactile sensitivity by site and for activities of interest here such as natural walking. Therefore, we had to fill this gap with experiments that would examine body locations that are of particular interest to wearable haptics and the effect of natural walking on sensitivity. We also included the effect of visual workload and expectation of locus of stimulus in our experiments.

Results from our two experiments, each with 16 participants, supported the following findings:

1. Increasing vibration intensity improves Detection Rate (DR) and reduces Reaction Time (RT).
2. Wrists and spine are the most sensitive in detecting vibrotactile signals, whereas feet and thighs are least sensitive. However, response time is similar across the body.
3. Walking significantly decreases DR and increases RT and it affects DR of thighs and feet more than other body locations.
4. Visual workload does not have any apparent effect on DR but it significantly impaired RT.
5. Expectation (*i.e.*, *a priori* knowledge about locus of stimulus), surprisingly, only reduced DR at wrists. However, it did significantly reduce RT.

6. Male participants had higher DR than female participants on the chest, stomach, wrists, and spine and females had better DR on thighs and feet. Also male participants had faster RT on all body locations except feet.
7. Participants preferred spine and wrists.

Based on these findings we concluded several design guidelines for creating wearable vibrotactile systems. These include recommendations on location of vibrotactile displays and intensity of vibrotactile cues, as well as considerations about movement, visual workload, and unexpectedness of cues; they are targeted at interaction designers, and generally anybody who wants to build a wearable vibrotactile system. These guidelines help designers build systems that are more successful at getting the user's attention (*i.e.*, increase Detection Rate) and faster response (*i.e.*, reduce Reaction Time) both of which are critical in design of vibrotactile systems (See Section 3.7.1).

Since we published this work in 2011 [78], it has been used in several areas such as spatial [26, 75, 117, 142], temporal [156, 157], and spatiotemporal guidance [99], as well as research on tactile sensation [2, 103, 108, 128, 129] and the development of a new tactile display [179].

### **7.1.2 Development and Evaluation of Robust Realtime Algorithm for Cadence Estimation (RRACE)**

In the second phase of this work (Chapter 4), we developed a cadence measurement algorithm that uses the 3-axis accelerometers that are available in smartphones these days, and through analysis of the accelerometer signals in the frequency domain, estimates the cadence of the user carrying the device (almost anywhere on his/her body). These are the main contributions from this phase:

1. We developed the RRACE algorithm, which is robust to user differences, orientation, and placement and works out of the box with no *a priori* knowledge or calibration.
2. We evaluated the performance of RRACE with four different window sizes on six body locations and at five different walking speeds.



3. We showed that RRACE can provide 95% or more accuracy on 4 out of the 6 body locations.
4. We compared RRACE with the readily available state-of-the-art *time-based* cadence estimation method and showed comprehensive evidence for the superiority of our algorithm.

There are two challenges that activity-related mobile applications face: hardware unpredictability and user differences; we developed RRACE with those in mind. RRACE is a cadence estimation instrument that liberates software developers and interaction designers from low-level signal processing challenges and helps them focus on high-level problems. This 2-year old work still stands as the most successful basis for an extensible algorithm that can be used by researchers. In fact, researchers in our lab have already extended it to a realtime gait analysis library called *GaitLib* [173] which is publicly available<sup>2</sup>. Many of the implementation issues are resolved in this library, which means that anybody with some programming background can skip the headaches associated with those challenges and easily build his/her creative ideas on top of the library. We believe RRACE and *GaitLib* can be used in a multitude of areas: cadence estimation and classification, guidance, activity monitoring, rehabilitation, and exercise games for kids and adults.

### 7.1.3 Study of Periodic Vibrotactile Guidance of Human Walking

In the last phase of this research (Chapters 5 and 6), we studied Periodic Vibrotactile Guidance (PVG) of human walking. First, we tested PVG in outdoor settings with five different rates with the effect of repetition on its performance. We anticipated that auditory multitasking would be the major source of problem for users' performance and we wanted to know how much workload PVG would impose on users, therefore, in the next experiment we added auditory task as a factor and used NASA Task Load Index (NASA-TLX) as a new instrument to measure workload. The contributions of this phase are the following:

1. The PVG system which uses tempo/interval between vibrotactile cues to

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<sup>2</sup><https://github.com/m-wu/gaitlib>

guide a user's cyclical movement (*e.g.*, walking) to achieve a desired speed.

2. Our two experiments showed evidence that most people are able to follow Periodic Vibrotactile Cues with 90% or above accuracy.
3. Our results showed that PVG successfully affected stride length and walking speed in addition to cadence.
4. Our data showed that, within the time range of our experiment, repetition did not significantly change the performance. This may mean that PVG is sufficiently simple for users with a very gentle (or no) learning curve.
5. We measured the effect of three different auditory tasks and found that, surprisingly, the auditory task most damaging to the performance of PVG was the verbal one (podcast), not the rhythmic one (techno music). However, we also found that the effect of auditory multitasking was not comparable to the guidance rate and therefore, the guidance signal could override the effect of auditory multitasking.
6. We also measured workload through self reports. Our findings suggest that PVG adds to the workload of walkers but the rate of guidance does not matter much. We also proposed a strategy to avoid harm to the user's safety based on our findings (See Section 6.7).

As far as we know, PVG of human walking is the first of its kind. Moreover, the ability of most users to follow the tempo of PVG when walking make us hopeful that it can be extended to other periodic movements such as cycling, swimming, or rowing. In addition to spatiotemporal guidance of commuters, PVG's applications include athletic training and rehabilitation. Ultimately, PVG can become a medium for sensory augmentation or substitution [74]; continuous usage may create an autonomous sense of speed based on goals or a feeling of space and time relative to future events. In fact, gadgets that create a sense of time have recently become available to consumers; *e.g.*, *Tikker* by Tikker Technologies LLC (Wilmington, DE, USA), "a watch that counts down your life" with a graphical display [161], and *Durr* by Skrekstore (Oslo, Norway), "a shivering bracelet that demonstrates how time seems to speed up and down" with vibrations at 5-minute intervals [148].

## 7.2 Secondary Research Contributions

The work presented in this dissertation made other contributions that might be useful for the research community; we did not list these contributions as primary because they were the by-product and not the main goal of the research. These contributions can be organized into two groups: (a) experimental design, methodology, and statistical analysis examples, and (b) the data.

### 7.2.1 Experimental Design and Methodology

This research is composed of six experiments. Most of these experiments had many factors and multiple levels in some factors. While we do not see complexity as a virtue, we hope that the methodologies we developed to deal with it here will be of use to others. Some of the challenges we faced are the following:

1. More levels in factors means longer experiments with results which are harder to interpret. However, if having more than two levels is necessary, we should consider an appropriate method for comparing levels in pairs. In our experiments we employed different pairwise comparisons such as Tukey test (Section 6.4.8), unpaired Z-test (Section 4.4.4), and post-hoc pairwise comparisons with Bonferroni adjustment (Section 5.4.6).
2. Counterbalancing the levels in repeated measures experiments is very important. It is not a difficult task for simple experiments (*e.g.*,  $2 \times 2$ ), however, it can be challenging for complex experiments particularly because we do not have access to a sufficiently large number of participants to test all the combinations. In the last experiment for example, we had to use two Latin-square designs crossed by each other to counterbalance both the order of auditory tasks and the guidance conditions.
3. Analyzing the results of complex experiments is orders of magnitude harder than simple experiments; the number of interaction effects grow exponentially with number of factors (*i.e.*,  $2^n - n - 1$  for  $n$  factors) and the growth of pairwise comparisons is cubic with regards to number of levels (*i.e.*,  $m(m-1)/2$  for  $m$  levels). In addition, with presence of interaction, additional steps must be taken in order to compare different conditions as in the

case of the last experiment in this work where we analyzed interactions in terms of simple effects (see Section 6.4.8).

4. Simple statistical methods such as Analysis of Variance (ANOVA) and t-test, which are widely taught and employed, are mostly not good matches for complex experiments. Data which do not satisfy the limiting assumptions of those tests (*e.g.*, binomial DR data of our first two experiments), and data which are missing not because of poor design but because of the nature of an experiment (*e.g.*, missing RT measurements when participants did not detect stimuli in the first two experiments) are just two examples. Other methods that are less known by the community should be employed in these situations.
5. Presenting the results of complex experiments is also a delicate matter. When there are several dependent variables, main effects, interaction effects, and pairwise comparisons, using the conventional methods of presenting the results of statistical tests (*e.g.*, reporting means and *p* values) makes the interpretation of the results and detecting high level patterns very hard. Each of the experiments we conducted faced this challenge in a unique way. For some examples of solutions see Figures 4.7 and 6.5 and Table 4.8.

### 7.2.2 Data

The six experiments that are presented in this dissertation involved vigorous data collection and preparation; *e.g.*, the Force Sensing Resistor (FSR) footfall detection used in Phase 2 and the RRACE algorithm used in Phase 3, for the measurements during experiments. On the other hand, because our data were collected from several sources (*e.g.*, accelerometer/cadence data from multiple phones in Phase 2 and 3), synchronizing and fusing multiple data sources took significant effort. We believe the data we collected can be of value for the scientific community and we have made our anonymized datasets public, and have likewise developed ethics protocols for this purpose which can be shared. This practice is rarely done which has contributed to our own challenges in examining our algorithm and more importantly comparing its performance with other algorithms. Therefore, we have

tried to contribute to a solution to this problem, by sharing carefully collected and measured datasets that others can test their own algorithms/ideas on. Our datasets are available for download at: <http://www.cs.ubc.ca/labs/spin/data/>.

In Phase 1 we produced Detection Rate (DR) and Reaction Time (RT) datasets:

1. DR and RT data of different vibration intensity, under different visual workload and movement conditions.
2. DR and RT data of different vibration intensity, under different expectation and movement conditions.

These can be used to create models of sensitivity to vibrotactile stimuli, which would enable designers to choose the appropriate intensity of vibration per location and condition.

In Phase 2 we produced accelerometer and cadence datasets that were collected by smartphones placed on six body locations:

1. Accelerometer, cadence, and Error Ratio (ER) data walking at different constrained speeds on treadmill.
2. Accelerometer, cadence, ER, and speed data of walking at different speeds outdoors.

These can be used for improving the existing cadence measurement algorithms or creating new ones.

In Phase 3 we produced two performance datasets and a workload dataset:

1. Cadence, speed, stride length, and ER data of walking under vibrotactile guidance at different tempos.
2. Cadence, speed, stride length, and ER data of walking under vibrotactile guidance and no guidance and during different auditory tasks.
3. NASA-TLX data for walking under vibrotactile guidance and no guidance and during different auditory tasks.

The performance data can be used for modeling of human cadence during auditory multitasking and under vibrotactile guidance. The workload data can be used for

modeling of physical and cognitive workload under guidance or no guidance and in presence or absence of auditory task during walking.

## **7.3 Reflections on Research Approach**

### **7.3.1 Visual Workload**

In our first experiment on sensitivity to vibrations of this dissertation we needed a visual task for users during parts of the experiment to measure the effect of visual workload on Detection Rate (DR) and Reaction Time (RT). The task we designed was counting the number of times a highlighted block hit the walls of a three-dimensional room on a large scale display (see 3.3.3). As shown in the results, the visual workload did not have any apparent effect on DR but significantly impaired RT.

We chose this task because (a) it was continuous, (b) had constant difficulty, (c) required attention and memory, and (d) was not so distracting to cause participants to stumble. We also faced the limitation of running the experiment indoors, therefore, we had to use a display screen.

At the higher level, we considered watching scenes that resembled walking in the real world (*e.g.*, video of cars and commuters) but we did not choose them for two reasons: firstly, watching a video passively with no real consequences would be too easy and we would have no control over users' engagement; secondly, the level of demand on users' attention would change during the video and there would be no way of keeping it constant. We even considered adding an extra task to watching a scene such as counting certain types of cars but decided against it because it no longer resembled a real world situation.

At the lower level, we used counting instead of immediate responses to visual stimuli (*i.e.*, requiring participants to react to every collision of the highlighted box with the wall) because we already had a respond to stimuli scheme for the vibrotactile signals and it would add unnecessary confusions in the experiment. Also, counting had an added bonus of engaging participants' memory.

It could be argued that the task we chose was not hard enough; while making the visual task too hard, would probably enable us to achieve significant effect of

visual workload on DR it would harm the external validity of our experiment by being too much harder than real world situations. An alternative approach to our abstract visual task would be to create a full-fledged walking simulation for engaging participants visually. Such an environment would only work if the participant's walking on the treadmill was linked to his/her movement in the virtual world. Apart from technical challenges of creating such a system which could drag us from our main goal without any definite return on investment, it would make it almost impossible to decouple the effect of movement from visual workload; in other words movement and visual workload would not be two separated factors because movement would affect the level of difficulty of the visual task with a very easy passive watching of a scene during the stationary condition and an active, relatively harder visual task during the walking condition.

### **7.3.2 Sensory Adaptation, Learning, and Fatigue**

Sensory adaptation is the change of responsiveness to a continuous stimulus over time [169] and tactile sensation is not immune from it [64]. Four of our experiments (out of six) were designed on the principle of responding to vibrotactile stimuli. In the sensitivity to vibrations experiments we tried to capture sensory adaptation by analyzing the relationship between DR and trial number. Our results suggested that the odds of detecting a vibration decreased by 6% after 100 trials. It is possible that learning has played a role by increasing the odds and canceling some of the effect of adaptation. Fatigue could also be a contributor. In the other two experiments, we found no significance for trial number which could also mean the overall effect of sensory adaptation, learning and fatigue has resulted in minimal effect on performance.

We did not try to separate sensory adaptation from learning and fatigue because they were out of the scope of this research; however, assuming that the length of the experiment contributes mostly to fatigue, number of stimuli to learning, and number of stimuli per locus of stimuli to sensory adaptation, we can propose an experiment to decouple them with three subject groups, *i.e.*, to solve the *3 unknowns* with *3 equations*. The three subject groups should be exposed to different levels of adaptation, learning, and fatigue.

**Group A:**  $2 \times m \times n$  stimuli on  $2n$  body locations in time  $t$ .

**Group B:**  $2 \times m \times n$  stimuli on  $n$  body locations in time  $t$ .

**Group C:**  $2 \times m \times n$  stimuli on  $n$  body locations in time  $2t$ .

Group A and B have equal length and equal number of stimuli but different number of stimuli per site ( $A:m$ ,  $B:2m$ ). Group B and C have equal number of stimuli and stimuli per site but different lengths. Comparing the effect of trial number on DR in A and B will reveal the effect of sensory adaptation relative to learning and fatigue, and the comparison between B and C will reveal the effect of fatigue relative to learning and sensory adaptation.

### 7.3.3 Step Detection

In order to validate RRACE we needed to test it with actual users to see how well it can estimate users' cadence. This is only possible when you have the ground truth for the cadence at each point in time. As explained in Chapter 4, we conducted a short indoor experiment on a treadmill and a full experiment outdoors, and one of the differences between the two was the cadence estimation that was used as the ground truth. In the first experiment, one experimenter visually detected footfalls on the treadmill and recorded them on the computer with the press of a button which registered the time of footfalls. In the second experiment, we placed FSR sensors in the participant's shoes and connected them to a small Arduino board carried by the participant which registered the timestamps of footfalls by comparing the force with a threshold that was determined during the calibration phase. In both of these methods, we measured the interval between two consecutive footfalls and inversed it to produce the gold standard cadence measurement, which was then compared with the estimation from RRACE.

Each of these methods has advantages and disadvantages. The manual step detection requires complete attentiveness of the experimenter and cannot be used when the participant gets too far from the experimenter; it is also prone to experimenter error. On the other hand, it is noninvasive and requires no setup for the participant. In contrast, the FSR system is immune from experimenter error and can be used outdoor where the participant can get very far from the experimenter;



however, the FSR system requires a setup procedure that includes calibration of the sensors for each user. Also, the FSR system (like any other invasive measurement tool) is prone to wearing out and breaking which is why we had a spare system during the experiment and eventually we had to replace one of the sensors with it. Another problem that may happen with sensors in shoes is that despite taping them inside the shoes, they may move inside which means that the range of the forces they measure may change and they may require a new calibration. Unfortunately, such incidents may not be known until after the experiment. In our post experiment data processing, we compared the timestamps from both feet and in cases where they did not match, we relied on the foot that seemed realistic and within a humanly possible range of cadence (*i.e.*, we ignored the data from the foot which were too fast or too slow). It should be noted that the errors in the ground truth cadence measurements in our experiments only made the performance results of RRACE appear worse than they actually were.

Although at this point we have already achieved a relatively noninvasive, accurate, and robust method for measuring cadence – *i.e.*, RRACE – we believe the FSR system is still of value in certain contexts, particularly when the temporal parameters such as time of footfalls are of interest and not just cadence; therefore, here we propose a few solutions for improvement of the FSR step detection:

1. Employing multiple sensors in each shoe and registering a footfall when the majority of sensors detect a threshold crossing (*e.g.*, 3 out of 5, or 2 out of 3).
2. Using the extreme pressure points in the near past (*e.g.*, last 10 seconds) to calibrate the threshold for detecting footfalls.
3. Creating an error detection method which alarms the experimenter about the possibility of a problem when the timing of footfalls (or the range of forces measured) seem out of ordinary (*e.g.*, too close or too far from each other).
4. Manual calibration of the sensors more frequently during the experiment.

We believe each of the above solutions, or a number of them combined, may improve the accuracy of the FSR footfall detection system.

### 7.3.4 Speed Measurement

Walking speed has been an important factor in all of our experiments. The first three experiments were conducted indoor and on a treadmill where the participants' walking speed was constrained by the speed of the treadmill (although chosen by the participant at the beginning of the first two experiments), and the rest of the experiments were conducted outdoor, where participants were given instructions or guidance cues but their speed was not physically constrained.

Treadmill solves the problem of speed measurement by displaying the speed but measuring the speed outdoor is not as trivial. Originally we planned to use an external Global Positioning System (GPS) receiver (connected to a phone) for measuring speed. However, the accuracy was not sufficiently high for measuring walking speed. Therefore, we chose to measure speed manually, by placing flags on the side of the sidewalk and measuring the elapsed time between the participant's crossing one flag to the next one. We used the same method with minor changes in the last experiment of this work too.

Unfortunately, the speed measurement method we used gives us the average speed over a trial and not the momentary speed at each point in time; as a result, the analysis on speed is based on the assumption that speed has remained constant during a trial. The downside to this is that the changes in speed, particularly at the beginning of a trial, will not be included in the speed analysis. This was not an issue in the experiment for validation of RRACE because we only needed to report the average speed of participants when instructed to walk at very slow, slow, typical, fast, and very fast speeds. The second experiment on vibrotactile guidance of human walking, was mainly focused on evaluating the effect of guidance on cadence, during auditory multitasking; speed was also analyzed to show the success of PVG system in affecting walking speed. We would argue that showing that PVG could affect the average speed over tens of seconds is sufficient for proving its success in real world scenarios where users might go from point to point in tens or hundreds of minutes.

### 7.3.5 Robust Realtime Algorithm for Cadence Estimation

In Chapter 4 we introduced Robust Realtime Algorithm for Cadence Estimation (RRACE), our in-house developed algorithm for cadence measurement. RRACE owes its robustness to three design choices:

1. operating in frequency-domain,
2. using Fast Calculation of the Lomb-Scargle Periodogram (FASPER) for handling time sampling irregularities,
3. feeding vector magnitude into the algorithm.

**Frequency-domain:** We used frequency domain instead of time domain because we were only interested in cadence and not timing of each footfall. In contrast with the time domain, the frequency domain is less concerned about the shape of the signal and more about the frequency at which the signal repeats itself; therefore, user differences and location on the body which mainly affect the shape and magnitude of the accelerometer readings do not affect the frequency domain as much.

**FASPER instead of Fast Fourier Transform (FFT):** We were fortunate to find out at a very early stage that the accelerometer data provided by most smartphones are not sampled at a constant rate, and the irregularities in the rate of sampling makes it impossible to do spectral analysis with FFT. Because trying to ‘repair’ the data – e.g., with interpolation – could introduce new sources of uncertainty, we decided to use FASPER to handle non-equispaced data.

**Vector Magnitude:** We assumed that users of our system would orient their phones in different ways and the orientation of the phone would even change with movement and the direction of the three accelerometer axes ( $x$ ,  $y$ ,  $z$ ) would not have any sort of consistency. The magnitude (Euclidean or L-2 norm) of the accelerometer vector, on the other hand, is independent of the orientation of the phone which is why we chose it for the spectral analysis instead of all of the axes.

The above design choices turned out to be successful in making RRACE work with acceptable accuracy on most body locations without requiring any calibration to account for user differences. Having said that RRACE has some imperfections too.

### **Weaknesses and Recommendations for Improvement**

As we showed in Section 4.4.6, RRACE consumed 10 times more power than *Endomondo* [33] and 5 times more than *Runtastic Pedometer* [137], the best activity measurement apps at the time. Although computation power of smartphones continues to increase and this problem will become less of a concern than it is right now, we believe by adjusting the window size and sampling frequency we can reduce the power consumption. For example, when the user is walking fast, the interval between the user's steps is shorter and therefore a smaller window size would be sufficient. On the other hand, when the user is walking slowly, the changes in acceleration are slower and therefore a less frequent sampling would be sufficient. The downside to reducing window size and sampling frequency is the negative effect on accuracy, therefore, the parameters of RRACE should be optimized to meet the requirements for both accuracy and power consumption. We should note that window size also directly affects latency, therefore, latency should also be considered in the trade-off between power consumption and accuracy.

When we developed RRACE we did not take advantage of any pre/post-processing methods such as filters. However, based on the typical range of step frequencies [88], we imagine that a 1-2.75Hz band-pass filter<sup>3</sup> would reduce most of the noise that is responsible for the error.

### **7.3.6 Choosing the Range for Cadence and Speed**

In experiments that involve requiring participants to walk, the experiment designer is faced with the question of how to choose the rate(s) in a way that reflects participant differences and meets the requirements for answering the research questions. In the six experiments we conducted we used five different methods (see Table 7.1).

#### **Phase 1, Experiments 1 and 2: Constrained but Flexible Speed**

Both experiments in Phase 1 were conducted indoors, using a treadmill. We asked each participant to choose a comfortable speed on the treadmill which was used during movement condition (*i.e.*, constrained their walking speed). As a result, some participants chose very slow speeds not to get too tired during the experiment.

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<sup>3</sup>A band-pass filter is a device that only allows frequencies within a certain range to pass through and blocks frequencies above and below that range.

To avoid unrealistically slow walking speeds on the treadmill, we can request participants to measure their typical walking speed prior to the experiment. Another suggestion is setting a lower limit on the walking speed which is less favourable because it is too artificial and may hurt the external validity of the experiment.

### **Phase 2, Experiment 1: Constrained and Inflexible Speeds**

In the first experiment of Phase 2, we wanted to test the RRACE algorithm at several constant speeds in addition to transitions from one speed to another. To make sure we have consistency among the participants we used the same selection of speeds for everyone. Using the same selection of speeds for all participants does not reflect the differences among them; the speed selection could be too slow for some and too fast for others. To avoid pushing the participants beyond their physical ability we had to choose the maximum speed conservatively.

### **Phase 2, Experiment 2: Unconstrained Speeds**

We conducted the second experiment of Phase 2 outdoors. The goal of the experiment was to examine our cadence estimation algorithm at a variety of speeds by a number of users. Without a treadmill, it was very hard to constrain walking speed of participants. We instructed participants to walk at five different speeds. By letting participants choose their walking speeds we tested our algorithm at many more levels which reflected the differences among the participants too.

### **Phase 3, Experiment 1: Cadence Guided with Unconstrained Range**

To test walkers' ability to follow vibrotactile cues we needed to use certain guidance tempos. In the first experiment of Phase 3 we instructed participants to walk at their fastest and slowest speeds first to measure the upper and lower bound for the tempo of guidance cues. Then we distributed the middle rates between those extremes. We believe this method reflects the diversity of participants better than any other method. However, the problem that may arise from this setup is that the guidance cues might end up being very close to each other (when the participant's fastest and slower speeds are not much different) or the opposite.

### **Phase 3, Experiment 2: Cadence Guided with Constrained Range**

In the second experiment of Phase 3 we only used two guidance rates in addition to a no guidance condition. In order to reflect the differences among participants to a

possible extent but to have the same distance (on a logarithmic scale) between the fast and slow guidance cues for everyone we decided to measure each participant’s typical (medium) cadence and set the fast and slow guidance tempos at a fixed ratio above and below it. This method allowed us to keep the same level of guidance difficulty for everyone in terms of divergence from typical cadence.

To summarize, we used many different methods for choosing speed(s) or cadence(s) during our experiments. Each of these methods tried to focus on different sets of requirements; some of them leaned more towards consistency, some leaned towards covering the differences among participants, and the rest tried to keep a balance between the two. If the length of an experiment, or added complexity were not an issue, one could even combine the above methods (*e.g.*, have a two part experiment with constrained and unconstrained speeds/cadences) to answer his/her research questions with more confidence.

**Table 7.1:** Method of choosing speed or cadence rates in our experiments.  $V$  denotes a speed rate (velocity) and  $F$ , a cadence rate (frequency).

Phase	Experiment	Location	Parameter	Rates	Chosen	By
1	1	Treadmill	Speed	$V_1$	$V_1$	Participant
	2	Treadmill	Speed	$V_1$	$V_1$	Participant
2	1	Treadmill	Speed	$V_1..V_{10}$	$V_1..V_{10}$	Experimenter
	2	Sidewalk	Speed	$V_1..V_5$	$V_1..V_5$	Participant
3	1	Sidewalk	Cadence	$F_1..F_5$	$F_1, F_5$	Participant
	2	Sidewalk	Cadence	$F_1..F_3$	$F_2$	Participant

### 7.3.7 Workload Measurement

In the second experiment of Phase 3 (Chapter 6) we used NASA-TLX to measure workload during different *guidance conditions* and *auditory tasks*. NASA-TLX is a subjective assessment that consists of two parts. Part 1 consisted of the six subscales addressing *mental demand*, *physical demand*, *temporal demand*, *performance*, *effort*, and *frustration*; the participant should rate each of these on a 100-points range with 5-points steps (discretized into 20 grades). Part 2 produces weightings for the above subscales by comparing them in pairs.

Our biggest challenge during that experiment was keeping it less than 1-hour, ideally at 45 minutes. We had to use NASA-TLX 12 times during the experiment.

To be as efficient as possible, instead of using the paper version, we used a computerized version of NASA-TLX which also made it easier for us to put the data from the whole experiment together. Using the computerized version especially makes the second part of the test easier. In fact, many researchers that do the test on paper only use the first part. The second part, which consists of 15 comparisons, only produces one total score and generally takes longer than the first part. As shown in the results, the patterns seen in the total score is not very much different from the subscales. Taking all these considerations into account, we believe the full NASA-TLX was too costly for our experiment.

## **7.4 Future Directions**

The work described in this dissertation can be expanded in various areas that will be explain in this section.

### **7.4.1 Susceptibility to Periodic Guidance in Other Movements**

Periodic guidance works on the premise of synchronizing a periodic movement with a repetitive cue to control the speed of the movement (for achieving a certain goal) through manipulation of the tempo of the cue. In that regard, periodic guidance does not necessarily rely on vibrotactile displays. As new tactile display technologies emerge, they can be used in periodic guidance too. As discussed before, in addition to walking, periodic guidance – PVG in particular – can also be used in other movements that are periodic too; examples are cycling, rowing, swimming, and dancing. It is interesting to see if periodic guidance is as successful for those applications as it is for walking. While these applications are more complex than walking, their users (*e.g.*, athletes or artists) would be more open to train themselves to improve their performance. Consequently, it is very important that for studying periodic guidance (or PVG) for those movements, we use longitudinal studies that allow us to provide sufficient training to the participants.

### **7.4.2 Study of PVG in Medium and Long Term**

Throughout this research we used several experiments to find answers to our research questions. Often times we faced experimental design choices that were

ultimately decided based on priority of research questions and our limitations. One of these experimental design decisions was the length of trials for the study of PVG which was explained in Chapters 5 and 6. Because we had various factors (*e.g.*, guidance rate, auditory distraction) and each had several levels and we could not allow each experiment to last longer than a certain amount of time, we had to limit trials to 60 or 25 seconds. As a result, we could not study PVG during longer periods of time. However, it is evident that in most applications, PVG could be used for several minutes or even hours. We believe a new set of experiment with as few factors and levels as possible and longer trials would enable us to evaluate PVG in more natural settings, where we can also see the effect of fatigue and learning to some extent. On the other hand, we envision PVG to be used several times a week or day; longitudinal studies of PVG that are conducted in several consecutive sessions can also help us analyze learning effects over time and give us a more realistic picture of how well users' performance can get if they get used to PVG over a longer period of time.

### **7.4.3 Effect of PVG on Attention**

Another interesting expansion of our work is measuring the extent to which PVG is taxing on the user's attention. This can be done through three methods. The first one is creating visual (or auditory) cues – *e.g.*, a blinking light – which are hard to detect and asking participants to respond to them [114, 120] at the same time that they are being guided by PVG. Detection Rate and Reaction Time can then be used to measure participants' attention. The second method is using recall performance; this can be done by planting objects along the route [110] or embedding words in an audio track, and asking participants to count them. The third method is using *Stroop test* [56, 102]; because both PVG and Stroop test compete for the participant's attention, lower score to the test under a certain condition indicates that PVG is more taxing on attention during that condition. It is worth noting that, since doing a Stroop test involves reading words (*e.g.*, name of a colour printed in the colour denoted or not denoted by the name), it cannot be used during walking in its conventional way; in order to use a Stroop test, we can give it to participants immediately after each trial (and when participants stop) or we can use an auditory



Stroop test [57, 107].

#### **7.4.4 Other Use Cases for RRACE**

In Chapter 4 we introduced RRACE, our algorithm for cadence estimation which uses the readily available accelerometer sensors in today's smartphones to measure a walker's stride frequency. RRACE works in frequency-domain, therefore, in principle it only cares about the frequency components of the signal, not its shape or phase. The downside of this characteristic is that RRACE, in its original form, cannot detect individual foot steps; however, as long as the signal has a major frequency component, RRACE can detect it. This means that RRACE can be used for detecting the frequency of other periodic movements such as pedaling or rowing too. By conducting experiments that are similar to the ones explained in Chapter 4 which focus on cycling, rowing, or swimming we might be able to verify this claim.

Another use case for RRACE is measuring speed and/or energy expenditure based on cadence. By measuring cadence, speed and/or energy expenditure we can create mathematical models that can estimate one factor based on one or two others. After we create such models, we can combine them with RRACE to create a new algorithm that estimates cadence from accelerometer signals and then computes speed and/or energy expenditure. The RRACE algorithm with the ability to measure speed can be used instead of or in addition to a GPS for improved accuracy of speed measurement or increased usability (*e.g.*, can measure speed even when there is no GPS satellite reception); the RRACE algorithm with energy expenditure estimation ability can be used for activity measurement applications.

#### **7.4.5 PVG's Performance in Closed-loop Control Settings**

In Chapter 1 we suggested two closed-loop settings that could be used to improve PVG's performance by reducing and compensating for the user's error. We also provided the results of those control systems in simulation settings to show how they differ in terms of dealing with error. The models we used for users were over simplified. We know that users can be very unpredictable in terms of how they react to cues, but we also know that they are much smarter than a simple mathematical model and will probably try to understand the guidance system to

respond better to it. Examining PVG in a control setting is a very interesting topic but it requires more than just one or two experiments. In order to explore PVG in a control setting, we need to design a controller that is stable and minimizes error. We can use past data on the user's cadence and speed and response to cues to create a loosely defined model then start with a very conservative controller (*i.e.*, imperfect in terms of error minimization but very stable) and improve it iteratively. Or, we can use Fuzzy [168] or other controllers [77] that do not rely on a perfect model of the system.

## **7.5 Closing Remarks**

Today's smartphones and other handheld devices are equipped with powerful computers, many kinds of sensors, and connectivity to the Internet. Having all these abilities in one very small package that can be taken virtually anywhere has opened the doors to many new applications – and guidance systems in particular – whose goal is making our lives easier. However, sometimes these applications become new causes for problems as a result of inappropriate usage or overloading of the audiovisual channels. In this dissertation, we proposed a new guidance method that employs periodic cues for fine-grained control of human movement through the tempo of the cues, which is very intuitive, does not abstract meanings, and works with minimal reliance on memory. The simplicity of periodic guidance enables it to use the tactile channel which has advantages over the audiovisual channels in certain contexts. Our research examined the use of vibrotactile displays in mobile contexts that are the focus of our guidance method, developed and verified a cadence estimation method that was required for periodic guidance of human walking and analyzed the performance of PVG, the vibrotactile version of our guidance system.

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## **Appendix A**

# **Supporting Materials: Detecting Vibrations Across the Body in Mobile Contexts**

This appendix contains the supporting materials regarding the experiments of Chapter 3.

### **A.1 Ethics Documents**

## Recruitment Email

THE UNIVERSITY OF BRITISH COLUMBIA



Department of Computer Science  
201-2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

# Vibration Perception in Mobile Contexts

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]

**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

Zoltan Foley-Fisher, M.A.Sc. Student, Dept. of Electrical and Computer Engineering

Version 1.0 / 07 July, 2010

The following recruitment emails will be sent to mailing lists maintained by the computer science department such as a list of graduate students and a list of persons who have expressed an interest in being study participants.

From: Idin Karuei and Zoltan Foley-Fisher  
Subject: Call for Study Participants - \$15 for Vibration Perception in Mobile Contexts study

The SPIN research group at the UBC Dept. of Computer Science is looking for participants for a study on the effect of movement on user's ability to detect and respond to tactile stimuli. You will receive a compensation of 15\$ for your participation in a single 1.5 hour session.

It is required that you wear sport shorts and short sleeve t-shirt (not tight).

We will attach small (M&M size) vibrators to your body on your wrists, upper arms, chest, back (upper spine), outer thighs, feet, and stomach. You will be walking on a treadmill for some parts of the study.

For more information or to sign up online, please visit: [REDACTED]

Please contact me if you have any questions.

Idin Karuei  
PhD Candidate, UBC Computer Science  
[REDACTED]

or

Zoltan Foley-Fisher  
M.A.Sc. Student, UBC Electrical and Computer Engineering  
[REDACTED]

## Experiment 1 Consent Form, Page 1/3



### THE UNIVERSITY OF BRITISH COLUMBIA

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C., V6T 1Z4

April 9, 2010

#### Consent Form (no videotaping)

Human-Computer Interaction Course Projects (CPSC 444/544/543)  
UBC Ethics Approval B03-0490

#### Principal\* and Co-Investigators

Dr. Kelly Booth, Prof., Dept. of Computer Science, UBC [REDACTED]  
Dr. Karon MacLean, Asst. Prof., Dept. of Computer Science, UBC [REDACTED]  
Dr. Joanna McGrenere\*, Asst. Prof., Dept. of Computer Science, UBC [REDACTED]  
Dr. Steven Wolfman, Asst. Prof., Dept. of Computer Science, UBC [REDACTED]

#### Student Investigators

Mohamed El-Zohairy, UBC [REDACTED]  
Zoltan Foley-Fisher, UBC [REDACTED]  
Idin Karuei, UBC [REDACTED]  
Sebastian Koch, UBC [REDACTED]  
Russ MacKenzie, UBC [REDACTED]

#### Project Purpose and Procedures

This course project is designed to investigate how people interact with certain types of interactive technology. Interactive technology includes applications that run on a standard desktop or laptop computer, such as a word processor, web browser, and email, as well as applications on handheld technology, such as the datebook on the Pocket PC, and also applications on more novel platforms such as a SmartBoard (electronic whiteboard) or a Diamond Touch tabletop display.

The purpose of this course project is to gather information that can help improve the design of

## Experiment 1 Consent Form, Page 2/3

interactive technology. You will be asked to use one or more forms of interactive technology to perform a number of tasks. We will observe you performing those tasks and analyze how the technology is used. You may be asked to complete a number of questionnaires and we may ask to interview you to find out your impressions of the technology. You will be asked to participate in at most 3 sessions, each lasting no more than 1 hour.

Although only a course project in its current form, this project may, at a later date, be extended by one or more of the student investigators to form the basis of his/her thesis research.

### **Confidentiality**

The identities of all people who participate will remain anonymous and will be kept confidential. Identifiable data will be stored securely in a locked metal filing cabinet or in a password protected computer account. All data from individual participants will be coded so that their anonymity will be protected in any project reports and presentations that result from this work.

### **Remuneration/Compensation**

We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

### **Contact Information About the Project**

If you have any questions or require further information about the project you may contact Professor Karon Maclean at [REDACTED].

### **Contact for information about the rights of research subjects**

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Information Line in the UBC Office of Research Services at 604-822-8598.

### **Consent**

We intend for your participation in this project to be pleasant and stress-free. Your participation is entirely voluntary and you may refuse to participate or withdraw from the study at any time.

Your signature below indicates that you have received a copy of this consent form for your own records.

Your signature indicates that you consent to participate in this project. You do not waive any legal rights by signing this consent form.

I, \_\_\_\_\_, agree to participate in the project as outlined above. My participation in this project is voluntary and I understand that I may withdraw at any time.

**Experiment 1 Consent Form, Page 3/3**

\_\_\_\_\_  
Participant's Signature

\_\_\_\_\_  
Date

\_\_\_\_\_  
Student Investigator's Signature

\_\_\_\_\_  
Date

## Experiment 2 Consent Form - Participant's Copy



### PARTICIPANT'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Vibration Perception in Mobile Contexts  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]

**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

Zoltan Foley-Fisher, M.A.Sc. Student, Dept. of Electrical and Computer Engineering

The purpose of this experiment is to examine and measure the effect of movement on user's ability to detect and respond to tactile stimuli.

In this experiment, you will be asked to press a mouse key whenever you feel a vibrotactile signal on your body while walking on a treadmill or sitting in a chair. You can choose a treadmill speed that is appropriate for you. You will be asked to attach tactors (i.e. non-invasive) to seven body sites: wrists, upper-arms, spine (between the shoulders), chest, outer thighs, stomach, and feet; these tactors will vibrate for short amount of time (i.e. 0.5s). Please tell the experimenter if you find the tactors uncomfortable and adjustments will be made. You will be asked to answer questions in a questionnaire as part of the experiment.

REIMBURSEMENT: \$15

TIME COMMITMENT: 1 × 90 minute session

CONFIDENTIALITY: *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

## Experiment 2 Consent Form - Researcher's Copy



### RESEARCHER'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Vibration Perception in Mobile Contexts  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
Zoltan Foley-Fisher, M.A.Sc. Student, Dept. of Electrical and Computer Engineering

The purpose of this experiment is to examine and measure the effect of movement on user's ability to detect and respond to tactile stimuli.

In this experiment, you will be asked to press a mouse key whenever you feel a vibrotactile signal on your body while walking on a treadmill or sitting in a chair. You can choose a treadmill speed that is appropriate for you. You will be asked to attach tactors (i.e. non-invasive) to seven body sites: wrists, upper-arms, spine (between the shoulders), chest, outer thighs, stomach, and feet; these tactors will vibrate for short amount of time (i.e. 0.5s). Please tell the experimenter if you find the tactors uncomfortable and adjustments will be made. You will be asked to answer questions in a questionnaire as part of the experiment.

**REIMBURSEMENT:** \$15  
**TIME COMMITMENT:** 1 × 90 minute session  
**CONFIDENTIALITY:** *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

You hereby CONSENT to participate and acknowledge RECEIPT of a copy of the consent form:

PRINTED NAME \_\_\_\_\_ DATE \_\_\_\_\_  
SIGNATURE \_\_\_\_\_



## A.2 Questionnaires

We used a pre-study questionnaire to collect information about participants and a post-study questionnaire to get their opinions after the experiment.

### Pre-study Questionnaire

1. In what age group are you?
  - 19 and under
  - 20-25
  - 26-30
  - 31-40
  - 40 and above
2. Gender
  - Male
  - Female
3. How many times in the last year did you use devices with tactile feedback (vibrating devices)?
  - Never
  - Once a month
  - Once a week
  - Few times a week
  - Once a day
  - Few times a day
4. How many times in the last year did you use a treadmill?
  - Never
  - Once a month

- Once a week
- Few times a week
- Once a day

5. Which hand is your dominant hand?

- Left
- Right

**Post-study Questionnaire**

1. Which vibration location was the most uncomfortable?
2. Which vibration location was the most comfortable?
3. For each location of vibration please choose the comfort level on a scale from 1 to 5; 1 being the most uncomfortable and 5 being the most comfortable.

Body location	1 - very uncomfortable	2 - uncomfortable	3 - neutral	4 - comfortable	5 - very comfortable
left shoulder					
right shoulder					
chest					
upper spine					
upper left arm					
upper right arm					
left wrist					
right wrist					
lower spine					
stomach					
left thigh					
right thigh					
left foot					
right foot					

4. If those motors were embedded in clothing items, which clothing item would you prefer they are embedded in? and why?
5. Do you have any comments?

## **Appendix B**

# **Supporting Materials: Cadence Measurement**

This appendix contains the supporting materials regarding the experiments of Chapter 4.

### **B.1 Ethics Documents**

## Consent Form Version 1.0 - Participant's Copy



### PARTICIPANT'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Gait Measurement Algorithm Verification  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]

**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
Bryan Stern, B.Sc. Student, Dept. of Computer Science

The purpose of this experiment is to test the gait measurement algorithm that we have developed on android phones.

In this experiment, you will be asked to walk on a treadmill. We will change the treadmill speed several times during the experiment; the changes will be smooth and of small magnitude. You will be asked to carry android phones in your front and back pocket and a backpack provided by us, attached to your arm and belt, and held in one of your hands.

**REIMBURSEMENT:** We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

**TIME COMMITMENT:** 1 × 30 minute session

**CONFIDENTIALITY:** *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

## Consent Form Version 1.0 - Researcher's Copy



### RESEARCHER'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Gait Measurement Algorithm Verification  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
Bryan Stern, B.Sc. Student, Dept. of Computer Science

The purpose of this experiment is to test the gait measurement algorithm that we have developed on android phones.

In this experiment, you will be asked to walk on a treadmill. We will change the treadmill speed several times during the experiment; the changes will be smooth and of small magnitude. You will be asked to carry android phones in your front and back pocket and a backpack provided by us, attached to your arm and belt, and held in one of your hands.

**REIMBURSEMENT:** We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

**TIME COMMITMENT:** 1 × 30 minute session

**CONFIDENTIALITY:** *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

You hereby CONSENT to participate and acknowledge RECEIPT of a copy of the consent form:

PRINTED NAME \_\_\_\_\_ DATE \_\_\_\_\_

SIGNATURE \_\_\_\_\_

## Consent Form Version 2.1 - Participant's Copy



### PARTICIPANT'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Gait Measurement Algorithm Verification  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]

**Co-investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

Oliver Schneider, M.Sc. Student, Dept. of Computer Science

Michelle Chuang, B.Sc. Student, Dept. of Computer Science

The purpose of this experiment is to test the gait measurement algorithm that we have developed on android phones.

In this experiment, you will be asked to walk on a sidewalk at different speeds ranging from very slow to brisk walking. You will be asked to carry android phones in your front and back pocket and a backpack provided by us, attached to your arm and belt, and held in one of your hands.

**REIMBURSEMENT:** We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

**TIME COMMITMENT:** 1 × 30 minute session

**CONFIDENTIALITY:** *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenters will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

## Consent Form Version 2.1 - Researcher's Copy



### RESEARCHER'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Gait Measurement Algorithm Verification  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
Oliver Schneider, M.Sc. Student, Dept. of Computer Science  
Michelle Chuang, B.Sc. Student, Dept. of Computer Science

The purpose of this experiment is to test the gait measurement algorithm that we have developed on android phones.

In this experiment, you will be asked to walk on a sidewalk at different speeds ranging from very slow to brisk walking. You will be asked to carry android phones in your front and back pocket and a backpack provided by us, attached to your arm and belt, and held in one of your hands.

**REIMBURSEMENT:** We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

**TIME COMMITMENT:** 1 × 30 minute session

**CONFIDENTIALITY:** *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenters will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

You hereby CONSENT to participate and acknowledge RECEIPT of a copy of the consent form:

PRINTED NAME \_\_\_\_\_ DATE \_\_\_\_\_

SIGNATURE \_\_\_\_\_

## **Appendix C**

# **Supporting Materials: Susceptibility to Periodic Vibrotactile Guidance of Human Cadence**

This appendix contains the supporting materials regarding the experiment of Chapter 5.

### **C.1 Ethics Documents**



## Recruitment Email

THE UNIVERSITY OF BRITISH COLUMBIA



Department of Computer Science  
201-2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

# Vibrotactile Guidance of Human Gait

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

Version 1.0 / 08 March, 2011

The following recruitment emails will be sent to mailing lists maintained by the Computer Science department or our research group, such as a list of department graduate students (often used for this kind of purpose) and a list of persons who have expressed an interest in being study participants.

From: Idin Karuei and Bryan Stern  
Subject: Call for Study Participants - \$10 for Vibrotactile Guidance of Human Gait

The SPIN Research Group in the UBC Dept. of Computer Science is looking for participants for a study on guiding users' walking speed. You will be compensated \$10 for your participation in a single 45 minute session.

We will attach small (the size of a penny) vibrators to your body on your wrists, upper arms, or back (upper spine). You will be walking freely outdoors in a safe place, such as an otherwise unused running track.

Please visit [REDACTED] to sign-up for the experiment.  
You can contact me if you have any questions.

Idin Karuei  
PhD Candidate, UBC Computer Science  
[REDACTED]

## Recruitment Poster

THE UNIVERSITY OF BRITISH COLUMBIA



Department of Computer Science  
201-2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

# Vibrotactile Guidance of Human Gait

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

Version 1.0 / 08 March, 2011

The SPIN Research Group in the UBC Dept. of Computer Science is looking for participants for a study on guiding users' walking speed. You will be compensated \$10 for your participation in a single 45 minute session.

We will attach small (the size of a penny) vibrators to your body on your wrists, upper arms, or back (upper spine). You will be walking freely outdoors in a safe place, such as an otherwise unused running track.

Please contact me to sign-up for the experiment.

Idin Karuei  
PhD Candidate, UBC Computer Science  
[REDACTED]

Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]

## Consent Form - Participant's Copy



### PARTICIPANT'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
fax: (604) 822-4231

**Project Title:** Vibrotactile Guidance of Human Gait  
(UBC Ethics #H01-80470)

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]

**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]

The purpose of this experiment is to test an algorithm developed to guide users to control their walking speed using vibrotactile displays and a smartphone's accelerometer.

In this experiment, you will be asked to synchronize your step frequency with vibrations that you feel on your body. These vibrations will be produced by a tactor that we will attach to your wrist, upper arm, or spine (between the shoulders). You will be asked to carry a smartphone in your front or back pocket or a backpack provided by us, attached to your arm or belt, or held in one of your hands.

REIMBURSEMENT: \$10

TIME COMMITMENT: 1 × 45 minute session

CONFIDENTIALITY: *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

## Consent Form - Researcher's Copy



### RESEARCHER'S COPY CONSENT FORM

Department of Computer Science  
2366 Main Mall  
Vancouver, B.C. Canada V6T 1Z4  
tel: (604) 822-3061  
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PRINTED NAME \_\_\_\_\_ DATE \_\_\_\_\_

SIGNATURE \_\_\_\_\_

## **Appendix D**

# **Supporting Materials: Periodic Vibrotactile Guidance of Human Cadence, Performance during Auditory Multitasking**

This appendix contains the supporting materials regarding the experiment of Chapter 6.

### **D.1 Ethics Documents**

## Recruitment Email

THE UNIVERSITY OF BRITISH COLUMBIA



Department of Computer Science  
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Vancouver, B.C. Canada V6T 1Z4  
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fax: (604) 822-4231

# Vibrotactile Guidance of Human Gait

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
James Bigland, B.Sc. Candidate, Cognitive Systems Cognition and Brain Option

Version 1.3 / February 21, 2013

The following recruitment emails will be sent to mailing lists maintained by the Computer Science department or our research group, such as a list of department graduate students (often used for this kind of purpose) and a list of persons who have expressed an interest in being study participants.

From: Idin Karuei and James Bigland  
Subject: Call for Study Participants - \$15 for Vibrotactile Guidance of Human Gait

The SPIN Research Group in the UBC Dept. of Computer Science is looking for participants for a study on guiding users' walking speed. Participants will require normal or corrected- to-normal (glasses / contacts), hearing, and be fluent in English. You will be compensated \$15 for your participation in a single 45 minute session.

In this experiment, you will be asked to synchronize your step frequency with vibrations that you feel on your body. These vibrations will be produced by a watch-like device we will put on your wrist. You will be asked to carry 4 smartphones in your pockets and a backpack provided by us. These phones will measure your step frequency. We may ask you to listen to an audio signal such as music, podcast, or sound of a metronome. We may ask you to talk while walking in response to a recorded dialog. We may ask you to read out loud a list of words while walking. We may also give you a set of questions at the end of each walk.

Please contact us to sign-up for the experiment.  
You can contact me if you have any questions.

Idin Karuei  
PhD Candidate, UBC Computer Science  
[REDACTED]

## Recruitment Poster

THE UNIVERSITY OF BRITISH COLUMBIA



Department of Computer Science  
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Vancouver, B.C. Canada V6T 1Z4  
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fax: (604) 822-4231

# Vibrotactile Guidance of Human Gait

**Principal Investigator:** Karon MacLean, Professor, Dept. of Computer Science, [REDACTED]  
**Co-Investigator:** Idin Karuei, PhD Candidate, Dept. of Computer Science, [REDACTED]  
James Bigland, B.Sc. Student, Cognitive Systems Cognition and Brain Option

Version 1.3 / February 21, 2013

The SPIN Research Group in the UBC Dept. of Computer Science is looking for participants for a study on guiding users' walking speed. Participants will require normal or corrected-to-normal vision (glasses/contacts), hearing, and be fluent in English. You will be compensated \$15 for your participation in a single 45 minute session.

In this experiment, you will be asked to synchronize your step frequency with vibrations that you feel on your body. These vibrations will be produced by a watch-like device we will put on your wrist. You will be asked to carry 4 smartphones in your pockets and a backpack provided by us. These phones will measure your step frequency. We may ask you to listen to an audio signal such as music, podcast, or sound of a metronome. We may ask you to talk while walking in response to a recorded dialog. We may ask you to read aloud a list of words while walking. We may also give you a set of questions at the end of each walk. Please contact us to sign-up for the experiment.

Idin Karuei  
PhD Candidate, UBC Computer Science  
[REDACTED]

Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
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Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]
Vibrotactile Guidance of Human Gait	[REDACTED]

## Consent Form - Participant's Copy



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James Bigland, B.Sc. Candidate, Cognitive Systems Cognition and Brain Option

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REIMBURSEMENT: \$15

TIME COMMITMENT: 1 × 45 minute session

CONFIDENTIALITY: *You will not be identified by name in any study reports. Raw data related to your performance and preference on computer-based tasks may be made publically available for use by the research community. Data made publically available will NOT include any video recording or other information that could identify you.*

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PRINTED NAME \_\_\_\_\_ DATE \_\_\_\_\_

SIGNATURE \_\_\_\_\_

## D.2 Experiment Setup

**Table D.1:** Tempos used for techno music conditions.

Tempo (Hz)	Tempo (BPM)	Index
2.645	158.7	8
2.554	153.3	7
2.466	148.0	6
2.382	142.9	5
2.300	138.0	4
2.221	133.3	3
2.145	128.7	2
2.071	124.3	1
2.000	120.0	0
1.931	115.9	-1
1.865	111.9	-2
1.801	108.1	-3
1.739	104.3	-4
1.679	100.8	-5

## D.3 NASA-TLX Screenshots

Task Questionnaire - Part 1

Click on each scale at the point that best indicates your experience of the task

**Mental Demand**  
 Low High  
 How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

**Physical Demand**  
 Low High  
 How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

**Temporal Demand**  
 Low High  
 How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

**Performance**  
 Good Poor  
 How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

**Effort**  
 Low High  
 How hard did you have to work (mentally and physically) to accomplish your level of performance?

**Frustration**  
 Low High  
 How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Continue >>

Task Questionnaire - Part 1

Click on each scale at the point that best indicates your experience of the task

**Mental Demand**  
 Low High  
 How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

**Physical Demand**  
 Low High  
 How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

**Temporal Demand**  
 Low High  
 How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

**Performance**  
 Good Poor  
 How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

**Effort**  
 Low High  
 How hard did you have to work (mentally and physically) to accomplish your level of performance?

**Frustration**  
 Low High  
 How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Continue >>

Figure D.1: NASA-TLX Screenshots - Part 1.

Task Questionnaire - Part 2

One each of the following 15 screens, click on the scale title that represents the more important contributor to workload for the task

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

<input type="button" value="Mental Demand"/>	How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?
or	
<input type="button" value="Effort"/>	How hard did you have to work (mentally and physically) to accomplish your level of performance?

**Figure D.2:** NASA-TLX Screenshots - Part 2 - 1/4.

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Performance      How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

Mental Demand      How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

---

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Temporal Demand      How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

Mental Demand      How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

---

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Temporal Demand      How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

Frustration      How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

---

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Frustration      How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

OR

Effort      How hard did you have to work (mentally and physically) to accomplish your level of performance?

---

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Physical Demand      How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

Frustration      How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Figure D.3: NASA-TLX Screenshots - Part 2 - 2/4 (blank space cropped).

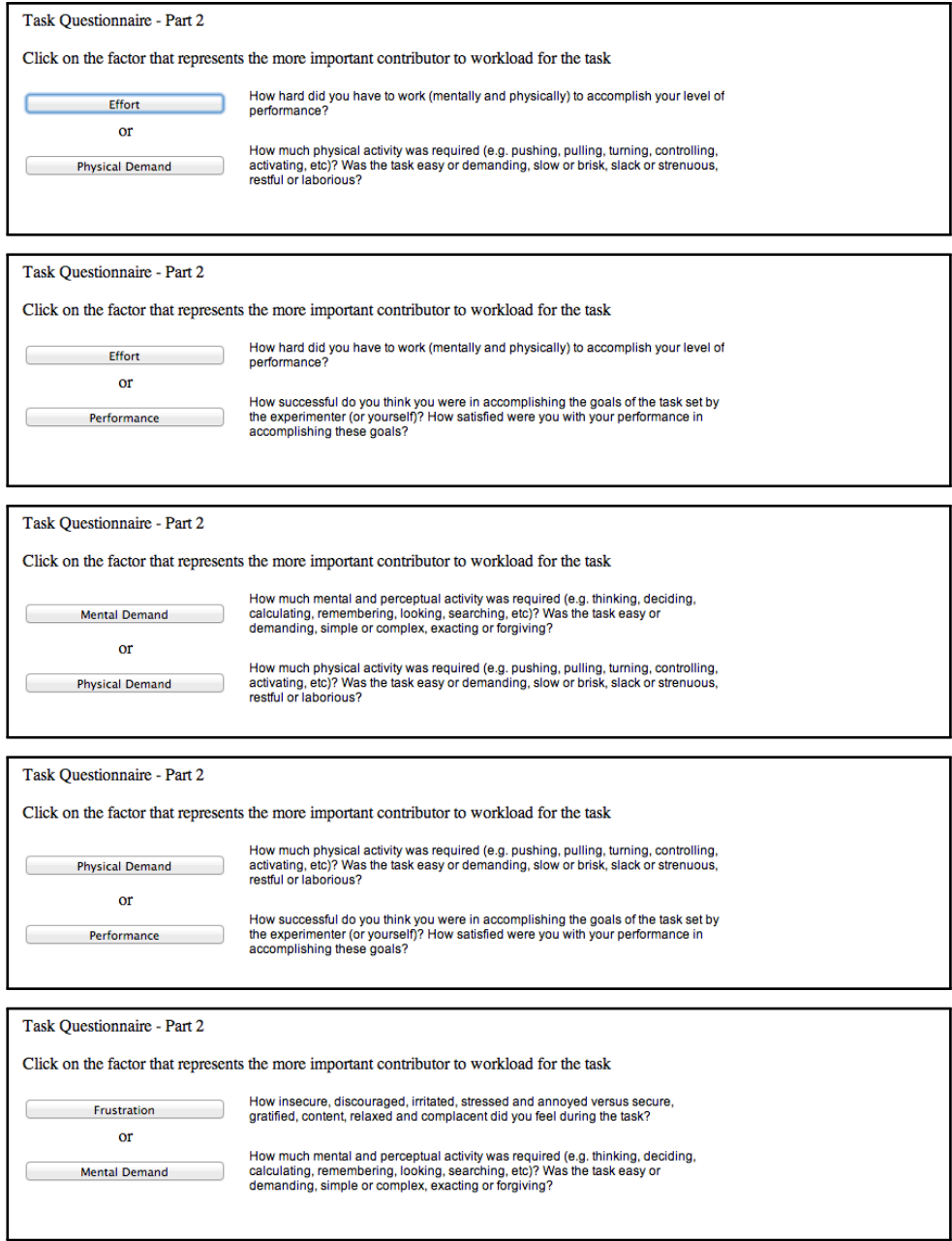


Figure D.4: NASA-TLX Screenshots - Part 2 - 3/4 (blank space cropped).

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Physical Demand      How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

Temporal Demand      How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Performance      How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

Frustration      How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Performance      How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

Temporal Demand      How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Task Questionnaire - Part 2

Click on the factor that represents the more important contributor to workload for the task

Temporal Demand      How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

Effort      How hard did you have to work (mentally and physically) to accomplish your level of performance?

**Figure D.5:** NASA-TLX Screenshots - Part 2 - 4/4 (blank space cropped).

	Rating	Tally	Weight
Mental Demand	65	3	0.2
Physical Demand	30	2	0.13333333333333333
Temporal Demand	45	5	0.33333333333333333
Performance	40	3	0.2
Effort	50	2	0.13333333333333333
Frustration	40	0	0
Overall	= 46.666666666666664		

**Figure D.6:** NASA-TLX Screenshots - Results (blank space cropped).

## D.4 Descriptive Statistics

**Table D.2:** Descriptive statistics of all metrics.

	<i>mean</i>	<i>median</i>	<i>SD</i>
age	25.958	24	10.187
weight (kg)	66.591	65.317	14.49
height (cm)	171.262	170.59	9.541
cadence error %	-15.792	-4.849	30.821
cadence	1.645	1.813	0.593
speed (mps)	1.339	1.32	0.246
speed ratio	0.952	0.962	0.128
stride length	0.699	0.687	0.117
mental demand	35.052	30	25.049
physical demand	29.688	20	23.387
temporal demand	33.524	25	24.47
performance	30.851	25	21.798
effort	37.153	30	24.282
frustration	23.906	15	20.536
tlx overall	35.281	30	21.556



**Table D.3:** Descriptive statistics of performance metrics by guidance condition.

	guidance	<i>mean</i>	<i>median</i>	<i>SD</i>
cadence error %	slow	-12.674	-0.014	34.256
	fast	-18.911	-11.516	26.592
cadence (Hz)	none	1.695	1.844	0.545
	slow	1.455	1.626	0.584
	fast	1.785	1.939	0.6
speed (mps)	none	1.38	1.349	0.205
	slow	1.195	1.15	0.195
	fast	1.44	1.402	0.263
speed ratio	none	0.98	0.99	0.074
	slow	0.851	0.847	0.104
	fast	1.024	1.038	0.129
stride length	none	0.721	0.712	0.096
	slow	0.622	0.61	0.079
	fast	0.752	0.738	0.127

**Table D.4:** Descriptive statistics of performance metrics by auditory task.

	audio	<i>mean</i>	<i>median</i>	<i>SD</i>
cadence error %	podcast	-18.226	-5.802	32.369
	techno	-12.468	-4.948	28.604
	classical	-19.155	-7.332	33.335
	silence	-13.32	-3.209	28.097
cadence (Hz)	podcast	1.593	1.753	0.614
	techno	1.717	1.815	0.537
	classical	1.579	1.752	0.65
	silence	1.691	1.844	0.553
speed (mps)	podcast	1.292	1.256	0.241
	techno	1.38	1.355	0.242
	classical	1.325	1.319	0.252
	silence	1.359	1.335	0.242
speed ratio	podcast	0.918	0.914	0.115
	techno	0.984	0.994	0.126
	classical	0.94	0.94	0.133
	silence	0.967	0.986	0.126
stride length	podcast	0.675	0.677	0.117
	techno	0.719	0.705	0.11
	classical	0.692	0.678	0.123
	silence	0.709	0.691	0.113

**Table D.5:** Descriptive statistics of workload scores by guidance condition.

	guidance	<i>mean</i>	<i>median</i>	<i>SD</i>
mental demand	none	21.823	15	18.283
	slow	39.531	30	25.926
	fast	43.802	35	24.791
physical demand	none	20.052	15	15.853
	slow	31.615	25	24.639
	fast	37.396	30	25.225
temporal demand	none	15.729	10	13.86
	slow	36.875	30	22.91
	fast	47.969	47.5	23.447
performance	none	20.312	15	18.336
	slow	32.5	25	19.841
	fast	39.74	35	22.599
effort	none	21.719	15	16.333
	slow	40.625	35	23.789
	fast	49.115	50	23.474
frustration	none	14.427	10	13.877
	slow	24.531	17.5	20.145
	fast	32.76	25	22.477
overall	none	20.694	17.333	13.586
	slow	38.361	32.5	21.402
	fast	46.788	48.333	20.068

**Table D.6:** Descriptive statistics of workload scores by auditory task.

	audio	<i>mean</i>	<i>median</i>	<i>SD</i>
mental demand	podcast	45.278	37.5	26.121
	techno	34.097	27.5	24.413
	classical	31.458	25	22.098
	silence	29.375	20	24.837
physical demand	podcast	33.125	22.5	26.649
	techno	29.097	22.5	21.169
	classical	28.194	20	23.002
	silence	28.333	20	22.518
temporal demand	podcast	37.014	27.5	27.162
	techno	33.75	25	23.493
	classical	33.056	30	23.204
	silence	30.278	22.5	23.852
performance	podcast	34.861	25	23.376
	techno	30.556	25	21.421
	classical	31.597	25	22.515
	silence	26.389	20	19.269
effort	podcast	43.125	40	25.83
	techno	37.222	30	23.793
	classical	33.472	25	23.053
	silence	34.792	30	23.727
frustration	podcast	27.569	20	22.782
	techno	24.583	20	20.824
	classical	22.5	17.5	18.576
	silence	20.972	15	19.548
overall	podcast	41.528	38.167	23.469
	techno	34.972	29.5	21.102
	classical	33.176	29.833	19.989
	silence	31.449	24.5	20.581

**Table D.7:** Mean *cadence error %* per each level of auditory task guidance condition.

	Slow Guidance	Fast Guidance
Podcast	-4.89%	-18.37%
Techno	0.27%	-14.83%
Classical	-7.96%	-17.00%
Silence	-4.36%	-13.37%

**Table D.8:** Mean *cadence (Hz)* per each guidance and auditory task condition.

	No Guidance	Slow Guidance	Fast Guidance
Podcast	1.72	1.60	1.81
Techno	1.85	1.67	1.88
Classical	1.74	1.54	1.83
Silence	1.81	1.60	1.91

**Table D.9:** Statistical significance of all performance metrics. Yes and No denote statistical significance and non-significance based on  $p < 0.05$ . GC and AT are short for guidance condition and auditory task.

Metric	Main Effects			Interaction Effects		
	GC	AT	Time	GC:AT	GC:Time	AT:Time
Cadence Error %	Yes	Yes	Yes	Yes	No	No
Cadence	Yes	Yes	Yes	Yes	Yes	No
Speed	Yes	Yes	N/A	No	N/A	N/A
Speed Ratio	Yes	Yes	N/A	No	N/A	N/A
Stride Length	Yes	Yes	N/A	No	N/A	N/A

**Table D.10:** Guidance condition's significant effect on cadence and pairwise comparisons of guidance conditions per each level of auditory task. Each two guidance conditions are significantly different from each other under every auditory task except no guidance and fast guidance under techno; cadence is fastest under fast guidance and slowest under slow guidance regardless of the auditory task.

Audio Subset	NG-SG	NG-FG	FG-SG	Order
Podcast	Yes	Yes	Yes	SG,NG,FG
Techno	Yes	No	Yes	SG,NG,FG
Classical	Yes	Yes	Yes	SG,NG,FG
Silence	Yes	Yes	Yes	SG,NG,FG

**Table D.11:** Statistical significance of all NASA-TLX scores and total workload. Significance is based on  $p < 0.05$ . NG, SG, and FG are short for No Guidance, Slow Guidance, and Fast Guidance respectively. P, S, C, and T are short for Podcast, Silence, Classical, and Techno; Significant difference between pairs of conditions are shown in columns 3 to 5 (guidance conditions) and 7 to 12 (auditory tasks).

	Guidance Condition				Auditory task						
	Sig.	NG-SG	NG-FG	FG-SG	Sig.	P-S	P-C	P-T	T-C	T-S	C-S
Mental Demand	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No
Physical Demand	Yes	Yes	Yes	No	No	-	-	-	-	-	-
Temporal Demand	Yes	Yes	Yes	No	No	-	-	-	-	-	-
Performance	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No
Effort	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No
Frustration	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No
Total Workload	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No