Epistemically Active Adaptive User Interfaces: Designing Subtly Interactive Adaptation Processes

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ABSTRACT

An accurate model of the user is one of the most important factors affecting the success of adaptive user interfaces. However, the input information from the user may not be sufficient for construction of accurate user models. We introduce the notion of epistemically active adaptive user interfaces that initiate subtle interactions with the user in order to collect new information about the user's state based on his responses (as in mixed initiative systems) or reactions to the probe. These epistemic actions can increase accuracy and decrease the computational cost of user modeling while requiring only low cost responses from the user.

We have proposed several strategies for designing epistemically active adaptive user interfaces and ultimately, we have defined the concept as a fuzzy set in which the degree of membership of adaptive interfaces is a function of interaction cost and informative value of the imposed interaction.

ACM Classification: H5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

General terms: Design, Human Factors

Keywords: adaptive user interfaces, user modeling, epistemic action, embodied cognition

INTRODUCTION

Adaptive user interfaces try to improve the user experience by tailoring the interface or information display to fit the user's current state as well as their background, expertise, needs and abilities. These systems must collect information about the user in order to build a user model that will determine the required adaptations [20,24].

Sources for data about user state may include user actions intended specifically to inform the system about state as well as analysis of normal user interaction. We distinguish between explicit self-reports, that is data that the user intentionally enter, such as age, disabilities, or personal preferences, with the intent to inform the system and in so doing to chance the style of the interface. Non-explicit inputs are those that are collected without adding a task for the user. These may come from a variety of sources such as control actions, camera input, and signals such as biopotentials [20]. The analysis and discovery of patterns in the collected data enables the system to draw conclusions about the user that are used to define the user model and to generate effective interface changes. If, as is frequently the case, user models are not correctly parameterized [13], the adaptive interface will fail to make correct decisions. Many of these potential failure situations can be identified by the nature of the algorithm underlying the adaptation mechanism. For example, conflicting decision rules in rule-based systems, and low confidence classifications in Bayesian learning systems indicate the possibility of making a wrong adaptation decision.

Accuracy of adaptive systems might be the most important factor in determining their success and the likelihood of their adoption. Accuracy of an adaptive interface is defined as the percentage of time that the correct interface is provided to the user [10,11] or the temporal and spatial settings of the interface are suitable for the user's characteristics (e.g. correct interface components are made visible, or the correct timing of interface events is chosen). In this paper, we propose that an effective strategy for design of adaptive interfaces will follow a quasi-scientific process. It begins with the choice of a candidate user model, after which a hypothesis is generated that states that a particular user response to a given subtle interaction probe might be expected. This is tested empirically and evaluated with respect to the model to generate an accuracy score for that model and in some cases estimates of the parameters of that model that best approximate the state of the user at a given point in their task. This work extends the initial definition of epistemically active adaptive user interfaces [26] and proposes strategies for applying the initial theoretical suggestions. The strategies are illustrated

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by examples, some of which are implemented in successful systems. Ultimately, the definition is formalized to some extent to support future refinements and extensions.

EMBODIED COGNITION AND EPISTEMIC ACTIONS

The embodied cognition approach focuses on the primary role of interaction in the cognitive processes of intelligent systems. Based on this perspective, the world of an agent is brought forth by the structural coupling of the agent and its environment [34]. Kirsh and Maglio found that Tetris players physically (as opposed to mentally) rotate zoids to save themselves computational effort [21] . The players modify the environment to speed-up matching the zoids and board, comparing to using and unaided pure mental process for rotating and matching them. In sum, they interact with and manipulate the physical environment to avoid errors and increase their performance comparing to processing mentally and manipulating mental representations. Human agents manipulate their environment to uncover information that is hard to process mentally. This perspective leads to considering interaction with the environment as an active component of cognition, thus avoiding redundantly modeling and creating representations of the environment [1,3].

Epistemic actions are implemented to improve the performance of pragmatic actions that actually implement a decision or plan, as when Tetris players rotate the tiles to simplify matching, or people sort the nuts and bolts before beginning an assembly task to accelerate the assembly process. Another example, which better matches the adaptive interfaces domain, happens when we want to find out if a dress fits. Three possible strategies can help you figure out if it fits. The first strategy is to try to match your mental representation of yourself with the dress by looking at it. This strategy is usually inaccurate, mentally expensive, but physically free. The second possible strategy is to wear the dress to make sure it fits (pragmatic action). This one is accurate, physically expensive, and mentally low-cost. Another possible strategy is to hold the dress in front of you to get a sense of how it fits. In this strategy, you are performing an epistemic action that provides more accuracy comparing to the first method (pure mental process), and less accuracy comparing to the pragmatic action. It also requires intermediate physical and mental cost comparing to the other strategies. Similarly, an adaptive interface aims at tailoring itself to the user and his environment.

Through performing epistemic actions, epistemically active adaptive user interfaces (EAAUIs) as intelligent agents make small changes in their world (the user) that facilitate processes that will be required to accomplish bigger or more important changes that directly support achieving the goal. Therefore, EAAUIs can be designed to initiate interactions with their world, the user, to collect information from the user's conscious or unconscious responses to subtle changes in the interface's appearance, behavior, or content, which can clarify the situations involving error-prone adaptation decisions. Explicit dialogues with user have been used in mixed-initiative systems; however, many possibilities for collecting information through subtle interactions have not yet been explored. Four sample strategies for leveraging epistemic actions in adaptive user interfaces are proposed and described through examples. The examples will be followed by discussions for better clarifying the concept of epistemically active adaptive user interfaces.

STRATEGIES FOR LEVERAGING EPISTEMIC ACTIONS IN ADAPTIVE USER INTERFACES

The goal of performing an epistemic action is to increase the accuracy of the future decisions and actions through low-cost negotiations and subtle interactions with the environment (figure 1). We focus on interaction techniques in the range of dialogue with the user as in adaptable interfaces [7], to "no imposed interaction" as in traditional adaptive interfaces that tend to predict user's situation based on pure observations. In the following sections, we describe some of the possible strategies for this range of interaction techniques.

Making subtle changes in the interface and deciding based on the user reactions

User reactions are one of the lowest cost interactions that the system may impose on the user. By making subtle changes in the interface or in the interaction process, which may or may not be noticeable for the user, the system is able to collect information about the user. We present this

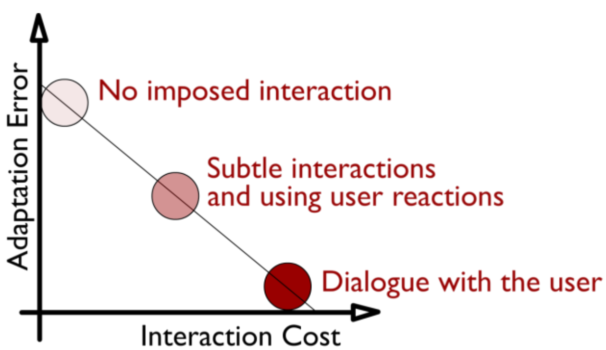

Figure 1. Subtle interactions may effectively decrease adaptation errors

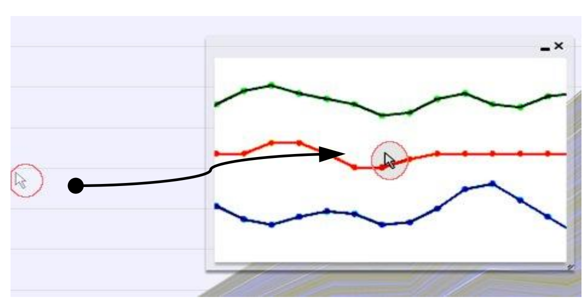

Figure 2. Epistemic action for dealing with "No interaction" state

Figure 3. Gradual cancelable adaptation by dimming the screen before turning it off

strategy based on our experience in designing an interruption manager.

Interruption managers are designed to find the right time for interrupting the user and delivering messages and notifications. Previous studies have shown the effectiveness of interruption managers that use various sensory information [9,16,19]. In order to manage interruptions in a web-based collaborative visualization system, we designed a prototype of an adaptive interruption manager that is aimed at minimizing the required sensory information for detecting interruptibility state by focusing on the interaction patterns and adapting the notifications to the state of the user. Reinforcement learning is used as the basic algorithm for mapping interaction patterns to interruptibility states; however, the user model, derived based on the interaction patterns, was insufficient for performing the right adaptation. One of the ambiguous user states is when the user is not interacting with the system: Sometimes the user was focused on the visualization or a text document, and sometimes, he was not paying attention to the screen; therefore, we should have distinguished the two states to make an appropriate decision. In the solution that we implemented, the adaptive interface disambiguates this situation by moving the cursor to the center of the component in focus (figure 2) to decide based on the user's reaction. A fast reaction in moving the cursor, means that he is focused on the workspace, but ignoring the cursor means that he is not paying attention to the screen.

Even considering special situations like the above, the adaptation errors were still common; therefore, we decided to use a general strategy to avoid costly interruptions. When an opportunity for delivery is detected, a permission dialog asks the user if he wants to see the message. Although this is a basic strategy in mixed initiative interfaces [14], it can also be considered as an epistemic action that can reduce the cost of a pragmatic action. However, it gets closer to the "dialogue with user" in the adaptation error/interaction cost diagram (figure 1). If an action is possibly costly, it makes sense to spend users' resources to avoid possible higher costs. . In the case of moving the cursor, a short interruption is used to avoid a possible attention-demanding task

Using gradual adaptation processes

Designing a gradual process for implementing an adaptation decision allows the user to cancel the wrong adaptation decision before becoming intrusive or harmful for the user's task. For example, most of the portable devices displays go off to save the battery energy after a certain period of idle time, assuming that the user is not working with the device. However, if the user is focusing on his task (e.g. reading a document), this adaptation to the user state, which is wrongly considered as idle, will be annoying and harmful for the user's performance. An example of this technique would be gradual dimming of the display before going off [5] (Figure 3). In this process, the user can easily cancel the wrong adaptation, by having a short and low-cost interaction with the device. This technique has already been implemented in various portable devices. The concept of "flexible automation" and allowing users to cancel or take control of an automated process has been around for years [35]. However, dimming of display is not just allowing the user to cancel or take control of the the automated process but it is a meaningful subtle interaction between the system and the user and most importantly this interaction is initiated by the system. The actual process of turning off the display is not yet started and the system interacts with the user to collect complementary information to reduce the uncertainty of the situation and the risk of performing the adaptation decision. We can take advantage of this epistemic action to enhance this interaction even more by updating the model of the user based on his delay in reacting to the probe. The idle time that indicates the user is not using the display can be updated, based on the reaction of the user to the dimming of display. For example if dimming the display after a sixty-second delay, is responded by the user, the wait-period should be increased to match with the user's task or situation that makes him not to interact with the device for more than sixty seconds.

Figure 4. Mixing adaptive and non-adaptive search results and leveraging user feedback

Mixing adaptive and non-adaptive content

Tailoring content to the user's needs is one of the major functions of adaptive user interfaces [20]. Mixing adaptive and non-adaptive content and monitoring the user's feedback, including choices and usage logs can be used for delivering adaptive content. For example, in an adaptive search engine, the results of adaptation can be mixed with non-adaptive results (figure 4) and the user's feedback can determine if the adaptive results are more desirable and the adaptation can be safely used or extended for the next set of results. Traditional search engines (which we consider them as non-adaptive systems) use the user's query to filter and order the search results. Adaptive search engines usually use one of these strategies: 1. ordering the search results based on the user's history 2. Augmenting the user's query by other keywords extracted based on user's history. In order to deal manage the possibility of error in adaptation, the system can mix the adaptive results with non-adaptive ones to use the user's feedback for verifying the adaptation decision. The result of verification can inform the decision about the next page/set of results. The interaction that is being imposed in this example is navigating the non-adaptive search-results that are filling the screen space and make it harder for the user to find the adaptive search-results that are probable more valuable to the user. This approach is different from relevance feedback in information retrieval systems [29,31], where the system takes advantage of user’s explicit or implicit feedback to the seemingly most relevant results based on the currently available information. In the suggested approach, the system adds few results that are not among the most relevant ones to the user’s query (thus imposing some cost) to better understand the user’s information need based on his reaction to those results.

Note that, we do not suggest mixing the adaptive search results with non-adaptive ones to ask the user to select one; the interface does that to be able to observe user behavior to make sense of his intention. It is about focusing on the subtle interactions, the space between asking the user and not interacting with him (pure observation).

Therefore, it is not about allowing the user to take over the hard parts of the task but the information that EAAUIs collect from the user's subtle feedback will help them to better perform their task (instead of asking the user to complement their task)

Multi-phase interaction and early feedback

Sometimes the interaction language between user and the user interface is so complex that the user interface might have problem understanding the user input. Voice and gesture interfaces are the exemplars of such interfaces [6,25]. Even touch screen keyboards pose considerable difficulty, which reduces users’ performance.

Researchers have proposed various techniques including tactile feedback [22], personalized alignment of keys [12], and pre-typing visual feedback [18], to deal with the usability issues of touch screen keyboards. In the latter technique, the interface is breaking the interaction into two phases to allow the user to fine-tune his input for achieving the desirable output. An adaptive touch-screen keyboard can use the user’s web history, or context of the word to disambiguate user input (e.g. due to fat finger problems). In this technique, showing the outcome of the disambiguation algorithm is an epistemic action before the pragmatic action of actually adding the character to the text. The user interface is taking this action to get a subtle informative feedback (confirm, cancel, modify), to inform the decision about which character should be added to the text. A variation of this technique is used in apple iPhone and iPod touch keyboards [28] (figure 5).

Figure 5. Multi-phase typing allows user to fine-tune his interaction

Adding a subtle confirmation phase to the interactions of adaptive user interfaces can improve user performance by allowing cancellation or clarification of ambiguous inputs. Through these interactions, an adaptive user interface can allow the user to alleviate the negative effects of inaccurate user modeling and prevent costly adaptation errors.

Designing EAAUIs

When an adaptive interface designer faces with a situation that the adaptations are prone to error, the designer can determine the information that having them can reduce the uncertainty and what is the interaction that is required for collecting the information. If the cost of obtaining the information is higher than desired, the information need may be able to be broken into smaller and easier to collect pieces of information that can reduce the uncertainty of the situation. The designer deals with a trade-off between accuracy of understanding the situation and the cost of imposed interaction. The examples provided in the previous sections, demonstrate some of the possible strategies for obtaining valuable information about the situation with low-cost subtle interactions.

CLARIFYING THE CONCEPT OF EPISTEMICALLY ACTIVE ADAPTIVE USER INTERFACES

Comparing the concept and goal of EAAUIs with those of mixed initiative systems, as a closely related framework, helps better clarifying the goal of this article. This comparison is followed by a definition of the concept of EAAUI.

Mixed Initiative Approaches

It is crucial to clarify how the concept of mixed-initiative systems is related to epistemically active adaptive user interfaces. Often frameworks overlap and the more specific ones share their assumptions with the more general ones, and make additional assumptions. "Mixed initiative" is broadly referred to "methods that explicitly support an efficient, natural interleaving of contributions by users and automated services aimed at converging on solutions to problems" [15]. This definition covers almost any kind of AI plus Human (also known as “human in the loop”) system and epistemically active adaptive user interfaces are a subset of them; however, the main characteristic of these interfaces is actively collecting information.

To better distinguish our approach from the more frequently explored area of mixed-initiative systems, we briefly review some of the mixed-initiative applications. A common theme in mixed initiative systems is to automate the task as much as possible and enable the user to edit, refine, or continue the task. This theme can be seen in Lookout [15], which was a scheduling assistant that could detect the need for invoking calendar system, and automate appointment generation, while allowing the user to change or refine the automated process' outcomes. Based on the cost/benefit analysis of automation, Lookout could decide if it needed to automate a process, do nothing, or ask the user if he needs help. A similar approach is used in Microsoft Windows Start Menu recent applications' list, which allows the user to pin his desired items to the list. Adaptive suggestions or adaptively supported adaptability [27] is another common theme in applying mixed initiative approach, which is applied in several studies such as suggesting additions and deletions of items for building customized toolbars [2,4,33].

An important characteristic of all of the aforementioned examples of mixed initiative systems is that they perform a part of the task that they can do with acceptable accuracy and allow or ask the user to finish the task by approving, modifying, or completing the output of the automated process. The concept of epistemically active adaptive user interface is not about allowing the user to take over the hard, complex, or uncertain parts of the task as in the exemplars of mixed initiative systems. Instead, it is about designing an adaptive interface as a live system that enters the world and actively manipulates it and maybe plays with the user while the user may or may not be aware of it, or implicitly negotiates with him, to make sense of his intention, situation, and the possible consequences of the various adaptation choices. After performing the epistemic action, the EAAUI can make a more accurate adaptation decision based on the collected information.

Although the focus of the concept of EAAUI can be well distinguished from the general approach of mixed-initiative systems, sometimes the strategy for performing an epistemic action can overlap with that approach.

A Semi-Formal Definition for Epistemically Active Adaptive User Interfaces

In this section, we present a semi-formal definition for epistemically active adaptive user interfaces by formalizing our understanding of them based on information theory and fuzzy sets theory.

An EAAUI can be referred to any adaptive interface that interacts with the user to inform its adaptation decisions for example by updating its user model. However, we believe that some of them can better represent the concept of EAAUI. For example we believe that the example of gradual dimming of the display or moving the cursor are better examples of EAAUI comparing to the adaptive keyboard example. The reason behind our comparison is that we believe that the interaction should be as subtle and low-cost as possible. Considering that some of the EAAUIs better represent the concept and implement in a more appropriate way, makes fuzzy sets theory an appropriate tool for defining them. Another theoretical background that can help the formalization process is prototypes theory [30]. The first two examples are the prototypical examples of EAAUIs, especially the example of moving the cursor for understanding the interruptibility state which led to the formation of the idea of EAAUIs. The two theories have some commonalities, however, the fuzzy set theory provides a more suitable foundation for possible future theoretical extensions; therefore in this article, we only focus on fuzzy sets theory. It is important to realize that the formalization that is followed is meant to model the conceptual space of EAAUIs rather than to be used as a computational device.

A fuzzy set is a class of objects with a continuum of grades of membership, which is characterized by a membership function that determines the membership grade of objects based on their features [36]. We believe EAAUI is a fuzzy set that various adaptive user interfaces can be members of it to some extent.

We have considered the following features to determine the membership function:

1. An adaptive interface can be an EAAUI if it initiates an interaction with the user to inform its adaptation decisions based on the users' response to the interaction.
2. The subtleness of interaction is important because the system should consider the user as an environment that can be explored and avoid having explicit dialogue with the user. This is also crucial from the perspective of adaptive user interface design, to aim for the usability goal of unobtrusiveness [20].
3. The subtle interaction with the user should lead to the information that can inform the adaptation decision as much as possible and decrease the uncertainty associated with the decision

We need to clarify the two concepts of subtleness and the informative value of interaction. Subtleness can be considered as the reverse function of interaction cost, which is a rather well known concept. There have been several efforts for modeling interaction cost for various types of user interfaces (e.g. [23] for visualizations and [17] for adaptive interfaces), which give us enough information for having a sufficient understanding of it.

Interaction cost is a function of:

1. Average cost of physical interaction (e.g. mouse movement, clicking),
2. Average cognitive load of the interaction,
3. The duration of the interaction that is required exclusively for the epistemic action (and is not part of the normal flow of user interaction), and

4. The amount of information that is blocked or hidden because of the imposed interaction, which is known as occlusion for visual information [23].

Depending on the type of adaptive interface and the epistemic action, a combination of these factors can determine the interaction cost.

We can refine our definition of interaction cost by determining an upper and lower bound for its value. Although the interaction cost is preferred to be closer to zero, it cannot take zero value; There should be some kind of imposed interaction with the user and only purely observing the user can result in zero interaction cost. Therefore, the lower bound for interaction cost of an epistemic action is zero. In order to determine the upper bound of interaction cost, we can consider adaptable interfaces , which enable the user to make the same adaptation decision. Adaptable interfaces provide mechanisms that allow the user to make adaptation decisions [8]. Therefore, the upper bound for the interaction cost of an epistemic action is the interaction cost associated with making the adaptation decisions by the user.

Based on the determined interval for an interaction cost, we can define normalized interaction cost (*NIC*) of an epistemic action *a*, for deciding about adaptation situation *s* as follows:

$$NIC_s(a) = \frac{IC(a)}{IC_{max}}$$

$$IC_{max} = \max_{s} IC(a_i) = IC(a_{adaptable\ in\ s})$$

NIC will be used, as the measure of interaction cost in the proposed membership function for EAAUIs the fuzzy set.

The second concept that can be formalized to some extent is the informative value of the information collected resulted from performing an epistemic action. In information theory [32], information is considered as a decrease in uncertainty. This perspective helps in measuring the information by comparing our uncertainty about a situation before and after receiving a piece of information. If we have a discrete variable X with n possible outcomes, that is:

$$X \in \{x_i\}, i \in \{1, 2, 3, \dots, n\}$$

Then the information content of x_i is defined as:

$$I(x_i) = \lg\frac{1}{p(x_i)} = -\log\ p(x_i)$$

This measure helps to evaluate the value of a piece of information that is an instance of a variable. However, what we usually need is to understand the value of knowing about a variable that may have various values. For example, we need to know if it is worth performing an epistemic action for learning about a variable such as an aspect of user state. The uncertainty about a variable determines the value of knowing its outcome, and it is quantified by information entropy. The entropy H of a discrete random variable is the expected value of the information content of *X*:

$$H(X) = E\big(I(X)\big) = \sum_{i=i}^{n} p(x_i)I(x_i)$$

$$= -\sum_{i=1}^{n} p(x_i)\log\ p(x_i)$$

If we can perform an epistemic action that provides us with the required information for making a correct adaptation decision, then the entropy of the variable that we are examining is all we need to decide about the informative value of our action. However, usually the information need is not readily available and we have to perform an epistemic action that can reveal some other variables that are related to the information need in some way. Therefore, we should estimate the difference between our uncertainty about our information need (i.e. knowing the correct adaptation) X and the remaining uncertainty of it after knowing about the variable that our epistemic action can reveal, *Y*. This is called mutual information and can be represented as follows:

$$I(X;Y) = H(X) - H(X|Y)$$

We can normalize this value to estimate the percentage of reduction in uncertainty in knowing the correct adaptation, X, due to knowing the user's response to the epistemic action, which is called normalized mutual information, but for the sake of simplicity, we call it normalized informative value (*NIV*) of performing an epistemic action *a* for deciding about adaptation situation *s*. That is:

$$X = User\ feedback\ to\ action\ \boldsymbol{a},$$

$$Y = Correct\ adaptation\ decision\ in\ situation\ \boldsymbol{s}$$

$$NIV_s(a) = \frac{I(X;Y)}{H(X)}$$

We need to estimate the value of $IV_s(a)$ to evaluate the value of performing an epistemic action. Therefore in designing an epistemically active adaptive user interface, the goal is to find an epistemic action with high $IV_s(a)$ (closer to 1) and low interaction cost (closer to 0).

Based on these concepts we can define a membership function that can characterize the fuzzy set of EAAUIs. Considering that all EAAUIs are mixed-initiative (in broad sense), we define the membership function of EAAUIs over the set of mixed initiative adaptive user interfaces, which maps each member of that set to a value between 0 and 1, determining the degree of their membership in the EAAUIs set.

We can map the set of EAAUIs to a vector space characterized by *NIC* and *NIV* as the two main dimensions of the space. Considering that both *NIV* and *NIC* are normalized variables, the EAAUIs space is a bounded

Example	Imposed Interaction and the associated costs	Informative value	Degree of membership in EAAUIs set
Interruption management	Moving the cursor and possibly blocking part of the visualization under the cursor and a short distraction	Medium: The user's response may not necessarily reveal the user's interruptibility state	Medium-high
Gradual dimming of screen	Moving the cursor, and removing some of the visual information and a short distraction	High: Almost always the user notices the dimming effect and his reaction clarifies if the display should go off	high
Adaptive search results	Screen-space that is filled with non-adaptive results, and physical cost of navigating them	Medium: The user's selection can be ambiguous if the user selects from both types of results or none of them	Medium-high
Touch keyboard	A fraction of a second if the initial selection is correct, otherwise less than a couple of seconds and slightly moving the finger	High: User can correct his selection in the second phase of the interaction	high

Table 1. Informative value and interaction cost of the EAAUI examples

space and hence the Euclidean distance of any two points is bounded:

$$v_i \in NIV, \qquad 0 \le v_i \le 1$$

$$c_i \in NIC, \qquad 0 \le c_i \le 1$$

$$E_i \in EAAUIs\,, \qquad E_1 = (v_1, c_1), E_2 = (v_2, c_2)$$

$$0 \le d(E_1, E_2) = \sqrt{(v_2 - v_1)^2 + (c_2 - c_1)^2} \le \sqrt{2}$$

We define normalized distance of two elements in this space as:

$$0 \le nd(E_1, E_2) = \sqrt{\frac{(v_2 - v_1)^2 + (c_2 - c_1)^2}{2}} \le 1$$

An EAAUI that performs an epistemic action with normalized informative value approaching to one, and normalized interaction cost approaching to zero can be considered as a reference point in our space, which presents a prototypical EAAUI. Having a prototype as a reference point can greatly facilitate the evaluation of other members' degree of membership. The normalized distance of an arbitrary user interface in this space from the reference point can be used as a simple measure for determining its degree of membership to the fuzzy set of EAAUIs; therefore, we define the membership function μ of the fuzzy set of EAAUIs as follows:

$$p = prototypical\ EAAUI\ (reference\ point) = (1, 0)$$

$$\mu : EAAUIs \to I = [0, 1]$$

$$\forall e \in EAAUIs$$

$$e = (v, c)$$

$$\mu(e) = nd(p, e) = \sqrt{\frac{(v - 1)^2 + c^2}{2}}$$

As we mentioned earlier, the formalization provided in this section is meant to be used for making sense of the conceptual space of EAAUIs rather than a computational tool, as it is challenging and maybe impossible to calculate the variables that are used in the formulas. Table 1 shows how informative value and interaction cost can help understanding the degree of membership of the example EAAUIs. We believe that the proposed semi-formal definition of epistemically active adaptive user interfaces can greatly clarify the concept, while providing a strong theoretical background based on information theory, fuzzy sets theory, prototypes theory, and vector space model, which enables further refinement or extension.

CONCLUSION

Adaptive user interfaces predict user state or context based on the information available to them, and the limited availability of the information makes many situations confusing for them. These confusions can be avoided by recognizing and addressing the error-prone situations. An epistemically active adaptive interface can effectively address these situations by actively probing its world (i.e. the user) in an experiment and analyzing the results in a quasi-scientific manner to increase its knowledge about the world. Epistemically active adaptive user interfaces can initiate subtle interactions with the user to resolve uncertainties about their hypotheses. They can take advantage of the user's conscious low-cost cooperation and feedback, or his unconscious feedback and reactions that can clarify the situation. We introduced four sample strategies for performing epistemic actions and described them through examples, some of which are implemented successfully in commercial systems. These subtle interactions may increase the accuracy of the adaptations, while imposing very little additional burden on the user. Design of future adaptive user interfaces can take advantage of similar strategies by actively engaging the user to enhance the user-model and bring about desirable interactions and accurate adaptations while avoiding the cost of possible wrong adaptation decisions.

Successful cases of epistemically active adaptive user interfaces such as the "gradual dimming of display" which is patented and implemented by nVidia, and widely used by various notebook manufacturers such as apple, demonstrate their possible value. However, clearly not all of instances on epistemically active adaptive user interfaces are/will be successful and the adaptive interface designers can think of them as another possible method that can help in dealing with the design challenges.

This article aims at inviting adaptive interface designers and researchers, to explore various possibilities in their specific domains and extend this work by their experiences. While acknowledging the fine line between subtle and annoying interactions, we believe many opportunities for improving the usability of adaptive interfaces through interacting with users are left unaddressed. Future works can reveal both the limitations and potentials of applying these techniques.

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