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User Affective State Assessment for HCI Systems

Xiangyang Li
University of Michigan-Dearborn

Qiang Ji
Rensselaer Polytechnic Institute

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Xiangyang Li
University of Michigan-Dearborn
xylum@umich.edu

Qiang Ji
Rensselaer Polytechnic Institute
qji@ecse.rpi.edu

ABSTRACT

HCI field began to see more studies in exploring not only the rational characteristics of human users in making decisions but also the “extra-rational” aspects in interacting with their environment and devices. The first task to exploit one such facet, human affect, is to accurately recognize and assess the affective state in real-time. This paper first serves as a survey of the state-of-the-art in affective state assessment, with focus on computational assessment models. Then a modeling framework developed by the authors based on dynamic Bayesian networks is introduced and compared with other models.

Keywords

HCI, user modeling, affective state assessment, computational model

INTRODUCTION

Human Computer Interaction (HCI) has moved from studies on friendly interfaces such as GUIs, to those that seek to understand, explain, justify, and augment user actions, focusing on developing more powerful representations and inferential machinery (Maes and Schneiderman, 1997). One important application is to design intelligent agents to provide personalized assistance to users in daily work and life (Hearst, 1999). Intelligent assistance systems have to reason, over time and under uncertainty, about the user’s internal state based on incomplete and multi-modal sensory observations.

User modeling has traditionally focused on what is generally considered ‘rational’ aspects of user behavior, typically the user’s knowledge and belief state. While useful, models focusing strictly on these aspects often miss critical components of user mental state and behavior: affective states. The affective states, often referred to as “extra-rational” factors, have been shown to strongly influence both reasoning and communication. For example, in every year many people are injured in car accidents because drivers are in status including fatigue, nervousness, or confusion. If we could detect these dangerous states in a timely manner, and provide appropriate assistance and alerts, we may prevent many accidents from happening.

Affective state assessment (ASA) could be considered as a pattern recognition or classification task. Current research work rarely uses analytical models from psychology and physiology to simulate human’s affective state appraisal process. In this paper, firstly, the measures used as the predictors to ASA are categorized. Then the methods and algorithms in processing these measures are introduced and discussed within ASA applications. Finally our approach based on dynamic Bayesian networks (DBN) to model the relationships among the affective state and the observed variables are described.

A lot of research efforts in ASA expand an extensive spectrum of psychology, physiology, linguistics, and computer science during the past several decades. The number of relevant systems and applications is too large to allow an exhaustic review. Thus the objective in this review is to summarize the past and current computational approaches in recognizing the affective state of a human subject, from external observable information of the subject and/or the surroundings.

MEASURES IN AFFECTIVE STATE ASSESSMENT

Human beings have abundant emotions in terms of sadness, happiness, guilty, pride, shame, anxiety, fear, anger, etc. Different categorizations of these emotions are used among researchers in different fields. Another helpful way of describing the emotion applies independent dimensions, such as valence and arousal (Schlosberg, 1954). Valence describes the “quality” of emotion, in terms of negative, neutral, and positive. Arousal describes the “energy degree,” which may be “activated” or “not activated.” Continuous values could be used for both dimensions.

The measures are informative modalities related to these state, i.e. the emotional, affective, or mental status. The information could be collected into discrete or continuous-valued variables with values evolving with time. To sympathize with the abundance of such measures, stretch our imagination to the context of active social setting of a conference or party. The physiological measurements, facial and body expression, behavior, wording choice and sentence organization in dialogue could all be indicators of a participant’s affective state. Even dressing could reflect the internal status prior to his/her arrival. Due to current limitation on acquisition and understanding of these measures, most research deals with only a few of them.

The measures could be verbal or nonverbal, and intrusive or non-intrusive. The following categorization is based on the nature of modalities and the acquisition instruments.

Self-report

Generally we consider self-report inapplicable in a practical user modeling and assistance system, where such interruption to the subject is normally at high risk or intolerable. However, self-report may be of interests in terms of direct query to the subject if we have tremendous concern about the recognition accuracy and prefer a very conservative assistance strategy.

Physiological Measures

Physiological measures mainly include EEG (Electroencephalography) on brain, EMG (Electromyography) on muscle, SC (Skin Conductance) or GSR (Galvanic Skin Response), GSA (General Somatic Activity) on human body, temperature, and other types of biophysical feedback such as heart rate, respiration, and perspiration.

Physical Appearance and Behavior

These mainly include the visual modalities of eye movement, facial expression, head gesture, body gesture, the acoustic expressions in voice intonation, pitch, and semantics in speech, and the domain specific behavioral modalities such mouse movement in operating a computer or steering features in driving a car.

Social and Problem-solving Strategy

Human beings' high level assessment of surroundings and decisions in choosing among alternative strategies often reflect the change of internal state. Using social and problem-solving strategies is difficult and highly domain dependent.

COMPUTATIONAL MODELS FOR AFFECTIVE STATE ASSESSMENT

Affect state assessment labels the current user state with certain affective category. Most computational models from statistics, machine learning, and pattern recognition could be possible candidates (Mitchell, 1997). Existing technologies include rule induction, fuzzy sets, case-based learning, linear regression models, discriminant analysis, hidden Markov model, neural networks, and Bayesian models.

Rule-based Systems

Rule based knowledge system describes in condition-consequence pairs the relationship between predictor values and target classes. In fact, models built from different algorithms could be transformed into IF-THEN rules and in assessment match the patterns represented by rules. However, because of the constraints in representation flexibility and modeling capability in the rule structure, researchers tend to ignore rule-based systems in feature-extraction and pattern recognition. A research of interest here is in facial expression recognition by Pantic et al (2002). Twenty rules were used to recognize the action units (AUs), defined in the Facial Action Coding System (FACS) (http://www-2.cs.cmu.edu/afs/cs/project/face/www/facs.htm). The input measures are the extracted mid-level feature parameters, e.g. distances between two points, describing the state and motion of the feature points and shapes in the face profile contour. The AUs, such as eyebrow raiser and lip corner depressor, relate to affective states closely and could be used in a higher-level model with affective states as output.

Fuzzy Sets

Fuzzy sets define the degree of membership of an element in a class. Then it defines the input membership functions and fuzzy rules to process inputs into rule strengths, representing the degree to agree on the consequence in each rule. These rule strengths are combined with output membership functions to get the output distribution. If necessary, a categorical class could be determined through defuzzification, e.g. as the center of distribution gravity. Hudlicka and McNeese (2002) used fuzzy rule knowledge base to assess the anxiety of a pilot from relevant static and dynamic data and observations including task context, external events, personality, individual history, training, and physiological data. In this research, fuzzy rules are matched to produce numerical anxiety weight factors (AWFs) for different modalities expressed in the data. Then these AWFs are used to compute an overall anxiety level. This resulting anxiety value is mapped into a three-valued qualitative categories, i.e., high, medium, or low. Other applications include emotion recognition using facial and voice data (Massaro, 2000). However, building up a complete and accurate rule base is an overwhelming task in a practical system.

Instance-based Learning

Case/instance based learning is very straightforward in designing a classifier. Classification is done by searching for the most similar representatives to the new case within a cases/instances pool. Scherer (1993) designed an emotional analyst expert system, GENESE, based on the component process appraisal model. The knowledge base consists of 14 vectors for 14 emotions, with quantified predictors for typical stimulus checks. In classification, subjects are asked 15 questions to provide the values for these checks. Then a Euclidean distance measure gives the distance of the new case to each emotion vector. The smaller this distance is, the more possible the current case belongs to the corresponding emotion. Similarly, Petrushin (2000) used k-nearest neighbors to predict emotions from a set of speech features. Instance/case based learning has strength in its natural way of designing classification algorithm and the decent performance in many applications. But the performance of instance-based learning depends on carefully picking the predictor features and the representatives in the baseline model.

Regression

Linear or nonlinear regressions in forms of logistic and probit regressions could be used in classification. In (Moriyama et. al, 1999), authors described an emotion recognition and synthesis system using speech data. In experiments, users repeat sentences in neutral and different emotional states. In training, the measured physical parameters about the pitch contour and power envelop of these speeches are transformed into principal component forms. Then these parameters are used to estimate the coefficients with these emotions as target variable, through multiple linear regressions. In recognition the input is the speech in the same words by the same person with unknown emotion or neutral state. The output is the emotion indication. Like other augmented algorithms in the family of regression, regression suffers the distribution assumption, the computation cost for complex data, and incomplete data.

Discriminant Analysis

Statistical discriminant analysis is based on comparing the Mahalanobi distances to different class centers. A Mahalanobi distance is the distance of the data point to the mean center of data points of the same class. Ark et al (1999) designed an emotion mouse to measure the user's affective state among happiness, surprise, anger, fear, sadness, and disgust. The four physiological measures are GSR, skin temperature, heart rate, and GSA. First the authors train a set of discriminant functions with the physiological measures as the predictors and the emotions as the classes. These functions are used to calculate the Mahalanobi distances to different emotion classes and accordingly to determine the membership of the current input. Again such algorithm is limited by its assumption of normal distribution. The reported prediction correct rate is only two thirds even in the case using the same training cases in testing data and no baseline normal cases in testing.

Neural Networks

Using connection weights, a collection of neurons could simulate complex input-output relations between different node layers. A series of neural networks (NN) applications exist in facial expression recognition such as in (Zhao and Kearney, 1996). Petrushin (1999, 2000a, 2000b) used acoustic features selected from human speech in call centers, including pitch, energy, speaking rate, formants, and also some descriptive statistics for them. The classifiers use a two-layer backpropagation neural network with 8, 10 or 14 input nodes, 10 or 20 nodes in the hidden sigmoid layer and 5 nodes in the output linear layer. This approach yields an average accuracy of about 65% in detection accuracy for emotional categories of normal, happiness, anger, sadness, and fear. In order to improve the performance, authors also used ensembles of NN classifiers applying voting strategy, and combinations of NN classifiers with each of them specially trained for only one emotion. Neural Networks have long achieved good performance in attacking many difficult problems. The disadvantages of them are mainly the required expertise in of the network structure and the training process, and the intense computation.

Bayesian Models

Bayesian approaches apply probability theory into system modeling and learning. Given the evidence, Bayesian theorem calculates the posterior probability of a hypothesis using the prior probability of hypothesis and the dependence of the evidence on the hypothesis. In (Qi and Picard, 2002; Qi et. al, 2001), authors described a Bayesian classifier to predict the frustration level of users using the features of mean and variance of the sensory pressure on the mouse. The data distributions are modeled by a mixture of Gaussians. The Bayesian classifiers are augmented by switching among component classifiers according to different contexts. The experimentation results show a little improvement compared with other global learning algorithms such as SVM, and are believed to be better than classical local learning algorithm such as k-nearest neighbors. Bayesian approaches provide a powerful modeling and prediction tool while normally the computation is intense. The Bayesian classifier in this case does not take the advantage of the conditional independency among variables. In the much more simplified form, naïve Bayes classifier is used to predict emotions (Sebe et. al, 2002).

Bayesian Networks

Bayesian networks use graphical models to summarize the prior knowledge of causal probability and conditional independency among the variables. Bayesian inference is used to update the beliefs on hidden and hypothetical variables based on the observation of external evidence. In (Ball and Breese, 2000; Breese and Ball, 1998), authors provided a Bayesian network to assess the user's affective state in terms of the dimensions of valence and arousal, and the personality in terms of the dimensions of dominance and friendliness, shown in figure 1. The observable information includes facial and body movements, and acoustic and speech data in terms of wording choice, speech characteristics, and input style characteristics. The network models the word selection more deeply by expanding it to an expression style including active, positive, terse, and strong expression, and an interpretation layer of used paraphrases. This research gives a good representation of a simple ASA model, although a more comprehensive Bayesian network model could be built to expand the representation structure both in depth and breadth.

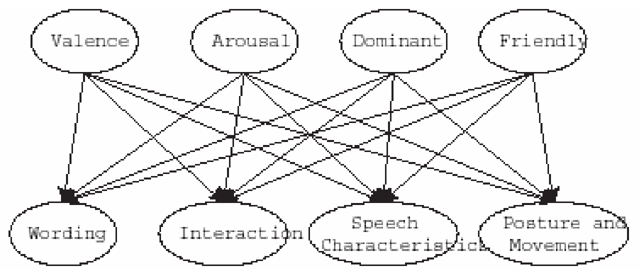

Figure 1. A Bayesian network for ASA using acoustic and visual observations (Breese and Ball, 1998)

Dynamic Bayesian networks (DBNs) add temporal causal links between hidden nodes in succeeding time slices. In (Conati, 2002; Conati and Zhou, 2002), authors designed a dynamic Bayesian network model for assessing students' emotion in educational games, shown in figure 2. Based on the OCC appraisal-based emotion theory (Ortony, Clore, and Collins, 1988), this network models the emotions, as the appraisal results of how the current situation fits with the person's goal and preference. There are also body expressions and physiological sensors to provide additional evidence, such as the visual information, EMG, GSR, and heart rate measures. The emotion states in this study include joy, distress, pride, shame, admiration, and reproach. Each time the student performs an action, or the agent offers a help, a new time slice is added to the network. This research tries to combine an analytical emotion model into an assessment model using physiological measures. But the simple addition of two paradigms in a single Bayesian network is rigid in nature, and sometimes may be inappropriate. The very fine grain size for describing the action and consequence is only appropriate for transient emotions when we consider the emotion of a user to some extent is stable. And the variant time interval between time slices may lead to requirement of developing time variant conditional probabilities. Furthermore in practice it is hard to know whether the action is satisfied or not.

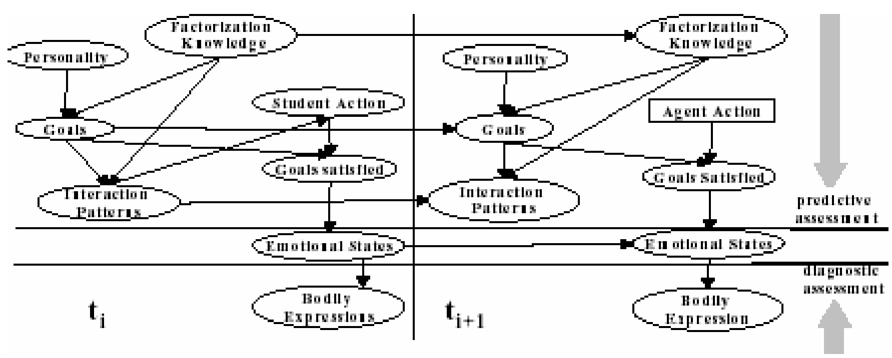

Figure 2. A Bayesian network ASA model in educational games (Conati and Zhou, 2002)

Hidden Markov Model

Hidden Markov Models (HMM) consider the situation where a Markov process is not directly observable. Instead, only observations from the involved states are observed. A HMM is in fact equivalent to dynamic Bayesian network representation. Picard (1997) conceptualized the use of HMM to model the emotion of users. The model has three emotional hidden states of interest, joy, and distress. The observation node could contain any sentic measures whose values change along with the underlying state. The transitional probability from one emotional state to another is defined and similarly the transmission probability of one measurement given each state. In (Cohen et. al, 2002; Cohen et. al, 2000), the authors used a multiple HMM model to classify six emotion classes including happy, angry, sad, surprise, disgust, and fear, shown in figure

3. The input is the AUs defined in FACS for facial expression. There are six 5-state HMM models to produce the state sequence from continuous AUs, one for each emotion. The high level HMM has seven states corresponding to the six emotions plus the neutral state. HMMs employ the Bayesian model in the basic form of two layer structure. They do not fully take into consideration the knowledge of other variables influenced by or influencing emotion states. Choosing the number of hidden states at the lower level HMM models is arbitrary, but important to the performance. The computational complexity will increase rapidly when more observation variables are combined into the model because of the full connections between them and the hypothesis variables.

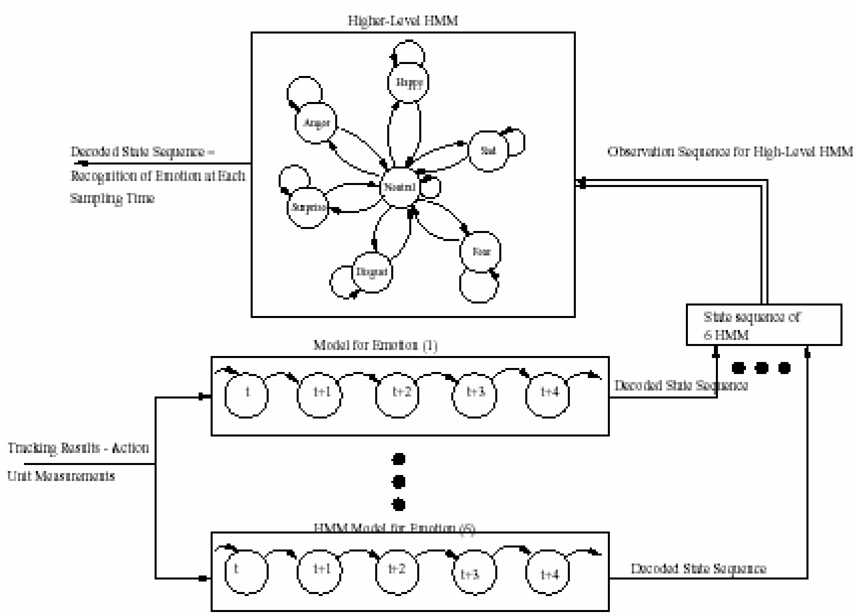

Figure 3. HMM ASA models using action units defined in FACS (Cohen et. al, 2000)

Discussions

Based on the analysis of existing computational models, we categorize them into two groups.

- The first group uses the observation measures as predictor variables and applies classification algorithms without the prior and context knowledge among these variables and the affective states. Such approaches include regression, discriminant analysis, Neural Networks, Bayesian classifiers, and instance-based learning. Similar to them, decision trees, EM algorithm, etc. are other potential candidates. The advantage of these algorithms is that they have very general and direct expression modeling ability in terms of numerical functions. In assessment, the models could be easily converted into rule-based expert systems. The disadvantages here include the lack of ability to handle uncertainty, complexity, and incompleteness involved in data sets. And they could not take the advantage of special domain features.
- The other group is represented by Bayesian networks and HMM models. They represent the prior domain knowledge and expertise into graphic network forms. By incorporating the relations among the subset of system variables, they also maintain the balance between the global and local representations. Thus the computational complexity could also be reduced. Some critics may dislike the domain knowledge necessary to build accurate models. However such knowledge provides powerful capabilities in handling the complex situation in practical systems in the form of the causal and uncertainty representations.

A GENERIC ASSESSMENT MODEL BASED ON DYNAMIC BAYESIAN NETWORKS

Bayesian networks are probabilistic graphical models representing joint probabilities of a set of random variables and their conditional independence relations (Pearl, 1988). The nodes characterize the hypothesis/goal variables, hidden state variables, and evidence/observation variables in the physical system, while the arcs linking these nodes represent the causal relations among these variables. Hypothesis nodes represent what we want to infer while the observation nodes represent sensory evidence. The intermediate hidden nodes are necessary to model the state generation process although in some cases they do not have explicit counterparts in the physical system. They link the hypothesis nodes with the observation nodes and therefore provide the flexibility in modeling the interdependency among them. Nodes are often arranged hierarchically at different levels, representing information at different abstraction levels. Static Bayesian Networks (SBNs) work with evidences and beliefs from a single time instant. As a result, SBNs are not particularly suited to modeling systems that evolve over time. DBNs have been developed to overcome this limitation, made up of interconnected time slices of SBNs. The relationships between two neighboring time slices are modeled by a Markov model, i.e., random variables at time *t* are affected by variables at time *t*, as well as by the corresponding random variables at time *t-1* only. The slice at the previous time provides diagnostic support, through its temporal links, for current slice and it is used in conjunction with current sensory data to infer the current hypothesis. DBNs represent a generalization of the conventional systems for modeling dynamic events such as Kalman filtering and Hidden Markov Models.

Bayesian networks have several advantages for modeling user's affective state. Firstly, BNs provide a hierarchical framework to systematically represent information from different and systematically account for their uncertainties. Furthermore, with the dependencies coded in the graphical model, Bayesian networks can handle situations where some data entries are missing. Secondly, the user's dynamically changing state and the surrounding situations call for a framework that not only captures the beliefs of current events, but also predicts the evolution of future scenarios. DBNs provide a very powerful tool for addressing this problem by providing a coherent and unified hierarchical probabilistic framework for sensory information representation, integration, and inference over time.

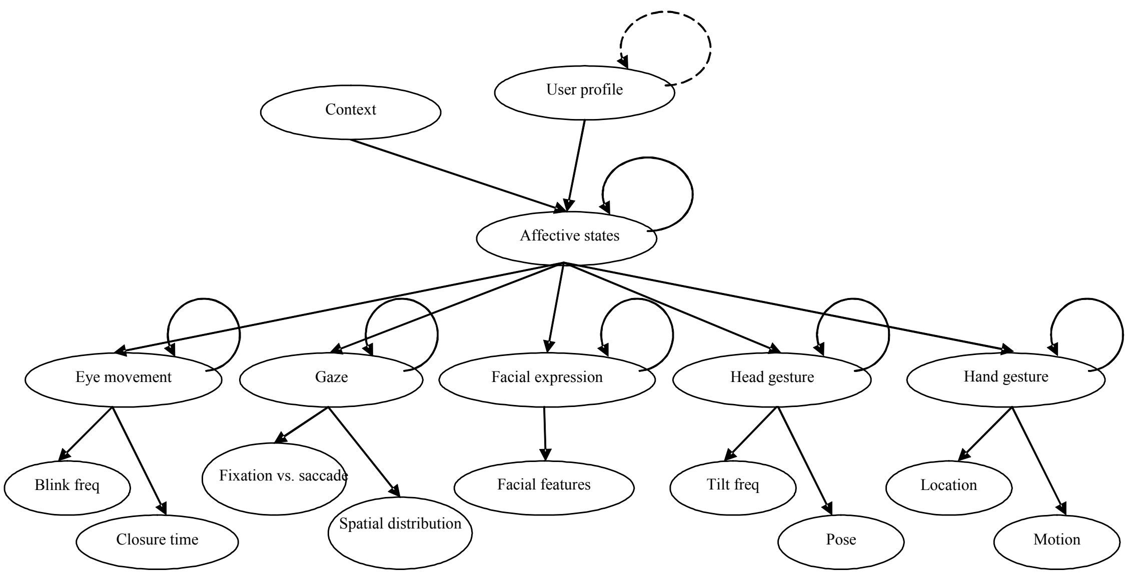

Figure 4. "Context-Profile-State-Observation" model, where self-pointing arrows indicate temporal links.

Our generic framework to apply dynamic Bayesian networks is the "Context-Affective State-Profile-Observation" model. It is used to infer the user's affective state from their observations. As in figure 4, this model captures the user's profile, affective state, and the contextual information.

- *Context component* represents information about the specific environmental factors that can influence the user's affective state, such as the driving situations and user interface features.
- *Affective state component* represents the user's affective status. Typical affective states include but not limited to fatigue, confused, frustration, fear, sad, and anger. While we list negative affective states of interest to safety, positive affects may be useful in applications as in entertainment.
- *Profile component* models user's personality, ability and competitiveness in finishing the operations. This provides the adaptation capability of the model to individual users.
- *Observation component* includes sensory observations of different modalities describing user behaviors. The figure shows some available visual modalities, while other such as verbal modalities could be used as well.

The affective state of the user and the hidden nodes of the user's visual, audio and behavioral status in current time slice are influenced by the corresponding variables in the most recent time slice. If we consider user profile unchangeable in a running session we use a dashed arrow to represent this setting. The context and profile variables influence the user's state. The user's states lead to the evolvement of visual, audio, and behavioral expressions.

Advantages

Our user affective assessment model provides a complete framework for user affective state assessment.

(1) Consideration of most relevant factors. In modeling the subject's internal or affective state, this model incorporates the context, profile information into account. On the other hand, different from the work by others previously discussed, we take in consideration the stability of the subject's affective state, and avoid the difficulty of depending on specific and transient task goals. We mainly rely on the power of external observations in recognizing subject's internal state, and let the accurate profile and other context information help to improve the accuracy through online and offline training.

(2) Integration of more and more evidence. Applying Bayesian network model in recognizing affective state has the advantage in handling the information uncertainty in multimodalities about the subject. More new evidences could be integrated into this model once we identify their relationship to the affective state. It needs only a little effort to combine the new modules with the legacy system but will provide us with more accurate view. This could also include more context and profile aspects, implemented by independent modules.

This framework combined with an active mechanism to engaging sensors shows satisfying detection accuracy and flexibility in configuration with other module in an intelligent user assistance system. More theoretical details and the report on performance of using simulated and real data are available in (Li and Ji, 2003; Li and Ji, 2004).

FUTURE DIRECTIONS AND CONCLUSION

We also notice that such an affective state assessment system alone could not fully fulfill very accurate assistance. We make such a statement since we observe that even with the carefully designed working procedures and paradigms, a single assessment model could not in some cases recognize the status of the subject very accurately and thus might fail to provide urgent assistance. This is especially true when we consider the variability of individual personality, the configuration complexity for the large number of node states, and the strict requirement on assistance systems.

In our view, there are two important directions that will greatly advance the whole area of affective state assessment and the intelligent user assistance in HCI field.

(1) *Integration of domain independent and dependent models*. Extended from the above discussion of applying Bayesian networks in assessing the affective state of human subjects, we could claim that such model is domain independent and thus could be used in different applications. In the meanwhile, a domain specific model is still necessary when we want to react to the subject's affect correctly and accurately. This model has functions similar to the "Affective Understanding" described by Affective Computing Research Group (2002) or the Belief Assessment component and the Impact Prediction component in ABAIS system by Hudlicka and McNeese (2002). Such a model is essential to provide "task environment awareness" for intelligent assistance. This domain dependent model captures the related application information, explains the causes of the problem, and predicts the impact of the problem in the task domain.

(2) *Integration of analytical and synthetic models*. Closely related to the above arguments, two weak points exist for a synthetic model and must be addressed when we design and implement a practical HCI system. One problem is raised when we need the details in understanding the affect and related problem. Based on only external observations, the grain size of Bayesian network models is normally not fine enough to fulfill this task. The other challenge is raised when we need to maintain the DBN model over the time and thus need to deal with the validity of the model and parameters. Thus we need a third party functioning as an objective judge. An analytical user model would be very helpful to provide insight into the interactions among user, interface, and environment.

We have begun the study integrating our modeling framework with cognitive models to push forward the advancement in these directions. An analytical cognitive model is a suitable candidate as the domain dependent model. Our future work will focus on the mechanisms to coordinate heterogeneous models in providing abilities of understanding and explanation of affective states, and in strengthening the user assistance efficiency.

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