Affective User Modeling for Adaptive Intelligent User Interfaces

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Abstract. In this paper we describe the User Modeling phase of our general research approach: developing Adaptive Intelligent User Interfaces to facilitate enhanced natural communication during the Human-Computer Interaction. Natural communication is established by recognizing users' affective states (i.e., emotions experienced by the users) and responding to those emotions by adapting to the current situation via an affective user model. Adaptation of the interface was designed to provide multi-modal feedback to the users about their current affective state and to respond to users' negative emotional states in order to compensate for the possible negative impacts of those emotions. Bayesian Belief Networks formalization was employed to develop the User Model to enable the intelligent system to appropriately adapt to the current context and situation by considering user-dependent factors, such as: personality traits and preferences.

Keywords: User Modeling, Bayesian Belief Networks, Intelligent Interfaces, Human Computer Interaction.

1 Introduction and Motivation

The field of Human-Computer Interaction (HCI) is defined as “a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them” [20] and Maybury [28] defines optimal human-computer interactions as ones where users are able to perform complex tasks more quickly and accurately, thus improving user satisfaction.

While interacting with an intelligent system each user's responses are different from other users [33]. This makes it necessary to build *user models* that will enable the system to record relevant user information in order to interact with its users appropriately. A User Model is defined as “the description and knowledge of the user maintained by the system” [33]. An adaptive system should modify the user model as the individual user changes, because each user differs from other users and the same specific user may change while s/he is interacting with the system.

Conventional user models are built on the knowledge level of the users about the specific context, what their skills and goals are, and the self-report about what they like or dislike. The applications of this traditional user modeling include student modeling [2] [10] [29] [36], news access [3], e-commerce [16], and health-care [37].

However, none of these conventional models accommodates a very important component of human intelligence: *Affect and Emotions*. People do not only emote, but they also are affected by their emotional states. Emotions influence various cognitive processes in humans (perception and organization of memory [5], categorization and preference [38], goal generation, evaluation, and decision-making [12], strategic planning [24], focus and attention [14], motivation and performance [8], intention [17], communication [4] [15], and learning [19]), as well as their interactions with computer systems [35]. The influence of affect on cognition and human-computer interaction increases the necessity in developing intelligent computer systems that understand users' emotional states, learn their preferences and personality, and respond accordingly.

Fig. 1. User Modeling Integrated with Emotion Recognition

The main objective of our research is to create Adaptive Intelligent User Interfaces that achieve the goals of human-computer interaction defined by Maybury [28] by performing real-time emotion recognition and adapting to the affective state of the user depending on the user dependent specifics such as personality traits or users' preferences and the current context and application. Although there are several possible applications of such systems, our current research interest focuses on the *Driving Safety* application. Previous research suggests that automobile drivers emote while driving in their cars [22] and their driving is affected by their negative emotions/states [18] [22] including anger, frustration, panic, boredom, or sleepiness. We aim to enhance driving safety with adaptive intelligent car interfaces that can recognize and adapt to the drivers' negative affective states.

We have been designing and conducting various in-lab and virtual reality experiments to elicit emotions from the participants and collect and analyze their physiological data in order to map human's physiological signals to their emotions [25] [26] [27] [30] [31]. After recognizing the user's emotion and giving feedback to her about her emotional state, the next step is adapting the intelligent system to the user's emotional state by also considering the current context and application and user dependent specifics, such as user's personality traits. Bayesian Belief Networks formalization was employed to create these user models in order to enable the intelligent system to adapt to user and application dependent specifics. Figure 1 represents our overall approach to the adaptive interaction of intelligent systems, by integrating emotion recognition from physiological signals with affective user modeling, in the specific case of driving safety application.

2 Related User Modeling Research

In the recent years, there has been a significant increase in the number of attempts to build user models that include affect at some level in the user model. Carofiglio and de Rosis' project [6] discusses the effect of emotions on an argumentation in a dialog, and models how emotions are activated and how the argumentation is adapted accordingly using Belief Networks. In the model, the user interacting with the system's agent is represented as the receiver. For example when a positive emotion "hope" is activated, the intensity of this emotion is influenced by the receiver's belief that a specific event will occur to self in the future, the event that the belief is desirable, and the belief that this situation favors achieving the agent's goal. The model represents both logical and emotional reasoning in the same structure. The model evaluates every candidate argument applying simulative reasoning by focusing on the current state of the dialog and by guessing the effect of the candidate on the receiver of argument. The difficulties encountered in some cases when classifying the argumentation as being 'rational' or 'emotional' increased the authors' belief in the importance of including emotional factors while creating natural argumentation systems. In this approach the assessment of the emotion is performed in the Bayesian Belief Network by activation of related cognitive components.

Affect and Belief Adaptive Interface System (ABAIS), created as a rule-based system by Hudlicka and McNeese [21], assesses pilots' affective states and active beliefs and takes adaptive precautions to compensate for their negative affects. The

architecture of this system is built on i) sensing the user's affective state and beliefs (User State Assessment Module), ii) inferring the potential effects of them on the user's performance (Impact Prediction Module), iii) selecting a strategy to compensate, and finally (Strategy Selection Module) iv) implementing this strategy (Graphical User Interface[GUI]/Decision Support System[DSS] Adaptation Module). Sensing the user's affective state and beliefs is defined as the most critical of the whole structure and it receives various data about the current user to identify his current affective state (e.g. high anxiety) and his beliefs (e.g. hostile aircraft approaching). The potential effects (generic effects and the task-specific effects) (e.g. task neglect) of the user's emotions and beliefs are inferred in the Impact Prediction Module using a rule-based reasoning. Rule-based reasoning is also used when selecting a counter strategy (e.g. present reminder of neglected tasks) to compensate the negative effects on the user's performance and finally the selected strategy is implemented in the GUI/DSS Module by using a rule-based reasoning to consider the individual pilot preferences.

Conati's [9] probabilistic user model, which was based on Dynamic Decision Networks (DDN), was built to represent the emotional state of users while interacting with an educational game by also including causes and effects of the emotion, as well as user's personality and goals. Probabilistic dependencies between causes, effects, and emotional states and their temporal evolution are represented by DDNs. DDNs are used due to their capability of modeling uncertain knowledge and environments to change over time.

Assessing users' emotional states is a very important component in both Hudlicka and McNeese's [21] and Conati's [8] models; however, none of these studies actually perform emotion recognition. Overall objective of our research is to perform both emotion recognition and appropriate interface adaptation and combine them in the same system. The adaptive intelligent user interface described in this article combines both the emotion recognition process and the modeling of user dependent factors such as emotions and personality traits.

3 Bayesian Belief Networks

Bayesian Belief Network (BBN) [34] is a directed acyclic graph, where each node represents a random discrete variable or uncertain quantity that can take two or more possible values. The directed arcs between the nodes represent the direct causal dependencies among these random variables.

The conditional probabilities that are assigned to these arcs determine the strength of the dependency between two variables. A Bayesian Belief Network can be defined by specifying:

1. Set of random variables: $\{X_1, X_2, X_3, \dots, X_n\}$.

2. Set of arcs among these random variables. The arcs should be directed and the graph should be acyclic. If there is an arc from X_1 to X_2 , X_1 is called as the parent of X_2 and X_2 is called as the child of X_1 .

3. Probability of each random variable that is dependent on the combination of its parents. For a random variable X_i , the set of its parents is represented as $\text{par}(X_i)$, and the conditional probability of X_i is defined as:

$$P(X_i | \text{par}(X_i))$$

4. If a node has no parents unconditional probabilities are used.

Unlike the traditional rule-based expert systems, BBNs are able to represent and reason with uncertain knowledge. They can update a belief in a particular case when new evidence is provided.

3.1 User Modeling with Bayesian Belief Networks

The Bayesian Belief Network representation of the User Model that records related affective user information in the driving environment is shown in Figure 2.

User model for the driving safety application is built as a decision support system. There are various parameters that would affect the optimal action that should be chosen by the adaptive interface. Some of the parameters (i.e. nodes) of the BBN are:

- Emotional state of the driver (represented by E, with 6 states: anger, frustration, panic, boredom, sleepiness, and non-negative);
- Driver's personality traits (represented by P, with 5 states: agreeable, conscientious, extravert, neurotic, open to experiments);
- Driver's age (represented by A, with 4 states: below 25, 25-40, 40-60, and above 60);
- Driver's gender (represented by G, with 2 states: female and male);
- Safeness of the current state (represented by S, with 2 states: no accident and accident).

Personality trait, age, and gender were chosen to be included in the model since previous studies suggest that they have influence on how people drive. For the model, possible emotions and states that a driver can experience are chosen as: Anger, Frustration, Panic, Boredom, and Sleepiness and their influence on one's driving are mentioned in section 1.

Personality traits of the driver were included in the user model, because previous studies suggest that personality differences result in different emotional responses and physiological arousal to the same stimuli [23], and the preferences of a person are affected by her personality [32]. Questionnaires can be used in order to successfully identify a driver's personality. Five-Factor-Model was chosen to determine the personality traits [11]. Following are the personality traits based on the Five-Factor-Model:

- Neuroticism (High neuroticism leads to violent and negative emotions and interferes with the ability to handle problems)
- Extraversion (High extravert people work in people oriented jobs, while low extravert people mostly work in task oriented jobs)
- Openness to experience (Open people are more liberal in their values)

- Agreeableness (High agreeable people are skeptical and mistrustful)
- Conscientiousness (High conscientious people are hard-working and energetic) [11].

Fig. 2. Bayesian Belief Network Representation of Driver Model

These personality traits also influence the way people are driving. Celler et al.'s study [7] show that Agreeableness have slight negative correlation with the number of driving tickets and Arthur and Graziano's study [1] showed that people with low Conscientiousness level have higher risk of being in a traffic accident.

Age and gender also have effect on people's driving [13]. Younger drivers are at a greater level of crash involvement (with a distinguished difference between 18-19-years-olds and 25-years-olds), more likely to take risks, they tend to show increased level social deviance, display the highest driving violation rates, and associate a lower level of risk perception, whereas older drivers tend to show a greater frequency of drowsy driving and tend to more likely suffer from visual impairments that affect their driving [13]. When it comes to gender differences, men are more likely to have accidents because of rule violations, and they make up majority of the aggressive drivers. Women on the other hand, are more likely to involve in crashes caused by perceptual or judgmental errors and they have lower driving confidence [13].

The node *Action* (represented by A) represents the possible actions (states) that can be taken by the interface. These actions include:

- Change the radio station
- Suggest the driver to stop the car and rest

- Roll down the window
- Suggest the driver to do a relaxation exercise
- Tell the driver to calm down
- Make a joke
- Splash some water on the driver's face

The node Utility (represented by U) represents the possible outcomes of the interface's chosen action in terms of an increase in the safety of the driver. This node is called the *utility node*, and the outcomes are called *utilities*. The three possible outcomes are:

- -1 (decrease in safety, i.e. decrease in probability for no accident),
- 0 (no change),
- 1 (increase in safety, i.e. increase in probability for no accident)

For example, if the driver was angry and the interface's action was suggesting the driver to do a relaxation exercise, and if this made the driver angrier, the outcome is negative 1. The variables determining this outcome are *Safety* and *Action*.

The posterior probability for *Safety* is calculated and it is used to calculate the *expected utility* of choosing each action. The action yielding the highest expected utility is chosen as the interface's action. The formula for the posterior probability of each state of *Safety* is given by:

$$P(S_i | E, P, A, G) = \frac{P(E, P, A, G | S_i)P(S_i)}{P(E, P, A, G | S_1)P(S_1) + P(E, P, A, G | S_2)P(S_2)} \quad (1)$$

Table 1. Actions with highest expected utility for different cases

Emotion	Personality Trait	Age	Gender	Safety	Interface Action
Anger (95%)	Conscientious (85%)	40-60	Female	Accident (14%)	Relaxation technique
Anger (70%)	Neurotic (90%)	Below 25	Male	Accident (6%)	Make a Joke
Sleepiness (95%)	Conscientious (95%)	25-40	Female	Accident (12%)	Suggest stopping the car and resting
Sleepiness (88%)	Neurotic (85%)	Below 25	Female	Accident (9%)	Change the radio station

The formula for the expected utility of each action is given by:

$$EU(A_i) = U(S_1, A_i)P(S_1 | E, P, A, G) + U(S_2, A_i)P(S_2 | E, P, A, G) \quad (2)$$

The reason for choosing Bayesian Belief Networks formalization to represent the user model in driving environment was BBN's ability to represent uncertain knowledge and to update a belief in a particular case when new evidence is provided.

3.2 Results

The driver model created with BBN for was tested by assigning various combinations of events with different probabilities to the network's variables. Table 1 shows the optimal action of the interface chosen by the BBN in four different cases.

4 Discussion

The strength of adaptive user interfaces lies in the fact that they are able to adapt to different users and different interactions based on the models that are built for users. An important component that influences users' interaction with computer systems is the user itself. Human-computer interaction is affected by various user dependent factors such as emotional states and personality traits. For this reason we built an adaptive user model with Bayesian Belief Network to record relevant affective user information.

User modeling is a very important part of adaptive interaction; however it is a difficult task especially when the existing real data is very limited. Affective knowledge is specifically restricted in the domain of driving safety. Currently our model is not complete due to the fact not all the functional dependencies can be calculated because of lack of enough real data. Our user model will be completed as a result of a collaborative effort of experts from the fields of Psychology and Transportation by determining the causal dependencies among the variables.

References

1. Arthur, W., Graziano, W.G.: The five-factor model, conscientiousness, and driving accident involvement. *Journal of Personality* 64, 593–618 (1996)
2. Barker, T., Jones, S., Britton, J., Messer, D.: The Use of a Co-operative Student Model of Learner Characteristics to Configure a Multimedia Application. *User Modeling and User-Adapted Interaction* 12, 207–241 (2002)
3. Billsus, D., Pazzani, M.J.: User Modeling for Adaptive News Access. *User. Modeling and User-Adapted Interaction* 10, 147–180 (2000)
4. Birdwhistle, R.: *Kinesics and Context: Essays on Body Motion and Communication*. University of Pennsylvania Press (1970)
5. Bower, G.: Mood and Memory. *American Psychologist* 36(2), 129–148 (1981)
6. Carofiglio, V., de Rosi, F.: Combining Logical with Emotional Reasoning in Natural Argumentation. In: *Proceedings of 9th International Conference on User Modeling - Assessing and Adapting to User Attitudes and Affect: Why, When, and How?*, Pittsburgh, PA, pp. 9–15 (June 2003)

7. Cellar, D.F., Nelson, Z.C., Yorke, C.M.: The Five-Factor Model and Driving Behavior: Personality and Involvement in Vehicular Accidents. *Psychological Results* 86, 454–456 (2000)
8. Colquitt, J.A., LePine, J.A., Noe, R.A.: Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology* 85, 678–707 (2000)
9. Conati, C.: Probabilistic Assessment of User's Emotions in Educational Games. *Journal of Applied Artificial Intelligence - special issue on Merging Cognition and Affect in HCI* 16(7-8), 555–575 (2003)
10. Corbett, A., McLaughlin, M., Scarpinato, S.C.: Modeling Student Knowledge: Cognitive Tutors in High School and College. *User Modeling and User-Adapted Interaction* 10, 81–108 (2000)
11. Costa, P.T., McCrae, R.R.: The Revised NEO Personality Inventory (NEO PI-R) professional manual. Psychological Assessment Resources, Odessa, FL (1992)
12. Damasio, A.: *Descartes' Error*. Avon Books, New-York, NY (1994)
13. Department of Transport: International review of the individual factors contributing to driving behavior. Technical report, Department for Transport (October 2003)
14. Derryberry, D., Tucker, D.: Neural Mechanisms of Emotion. *Journal of Consulting and Clinical Psychology* 60(3), 329–337 (1992)
15. Ekman, P., Friesen, W.V.: *Unmasking the Face: A Guide to Recognizing Emotions from Facial Expressions*. Prentice Hall, Inc, New Jersey (1975)
16. Fink, J., Cobsa, A.: A Review and Analysis of Commercial User Modeling Servers for Personalization on the World Wide Web. *User Modeling and User-Adapted Interaction* 10, 209–249 (2000)
17. Frijda, N.H.: *The Emotions*. Cambridge University Press, New York (1986)
18. Fuller, R., Santos, J.A. (eds.): *Human Factors for Highway Engineers*. Elsevier Science, Oxford, UK (2002)
19. Goleman, D.: *Emotional Intelligence*. Bantam Books, New York (1995)
20. Hewett, T., Baecker, R., Card, S., Gasen, J., Mantei, M., Perlman, G., Strong, G., Verplank, W.: ACM SIGCHI, Curricula for Human-computer Interaction. Report of the ACM SIGCHI Curriculum Development Group, ACM (1992)
21. Hudlicka, E., McNeese, M.D.: Assessment of User Affective and Belief States for Interface Adaptation: Application to an Air Force Pilot Task. *User Modeling and User-Adapted Interaction* 12, 1–47 (2002)
22. James, L.: *Road Rage and Aggressive Driving*. Prometheus Books, Amherst, NY (2000)
23. Kahneman, D.: Arousal and attention in: *Attention and Effort*, pp. 28–49. Prentice-Hall, Englewood Cliffs, N.J (1973)
24. Ledoux, J.: Brain Mechanisms of Emotion and Emotional Learning. *Current Opinion in Neurobiology* 2, 191–197 (1992)
25. Lisetti, C.L., Nasoz, F.: MAUI: A Multimodal Affective User Interface. In: *Proceedings of the ACM Multimedia International Conference*, Juan les Pins, France (December 2002)
26. Lisetti, C.L., Nasoz, F.: Using Non-invasive Wearable Computers to Recognize Human Emotions from Physiological Signals. *EURASIP Journal on Applied Signal Processing - Special Issue on Multimedia Human-Computer Interface* 11, 1672–1687 (2004)
27. Lisetti, C.L., Nasoz, F.: Affective Intelligent Car Interfaces with Emotion Recognition for Enhanced Driving Safety (*Invited). In: *Proceedings of 11th International Conference on Human-Computer Interaction*, July 2005, Las Vegas, Nevada, USA (2005)

28. Maybury, M.T.: Human Computer Interaction: State of the Art and Further Development in the International Context - North America (Invited talk). In: International Status Conference on MTI Program, Saarbruecken, Germany (October 26-27, 2001)
29. Millan, E., Perez-de-la Cruz, J.L.: A Bayesian Diagnostic Algorithm for Student Modeling and its Evaluation. *User Modeling and User-Adapted Interaction* 12, 281–330 (2002)
30. Nasoz, F., Lisetti, C.L.: MAUI avatars: Mirroring the User's Sensed Emotions via Expressive Multi-ethnic Facial Avatars. *Journal of Visual Languages and Computing* 17(5), 430–444 (2006)
31. Nasoz, F., Alvarez, K., Lisetti, C.L., Finkelstein, N.: Emotion Recognition from Physiological Signals for Presence Technologies. *International Journal of Cognition, Technology, and Work – Special Issue on Presence* 6(1) (2003)
32. Nass, C., Lee, K.M.: Does computer-generated speech manifest personality? An experimental test of similarity-attraction. In: *Proceedings of the CHI 2000 Conference*, The Hague, The Netherlands (April 1-6, 2000)
33. Norcio, A.F., Stanley, J.: Adaptive Human-Computer Interfaces: A Literature Survey and Perspective. *IEEE Transactions on Systems, Man, and Cybernetics* 19(2), 399–408 (1989)
34. Pearl, J.: *Probabilistic Reasoning in Expert Systems: Networks of Plausible Inference*. Morgan Kaufmann Publishers, Inc., San Francisco (1988)
35. Reeves, B., Nass, C.I.: *The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places*. Cambridge University Press, Cambridge
36. Selker, T.: A Teaching Agent that Learns. *Communications of the ACM* 37(7), 92–99 (1994)
37. Warren, J.R., Frankel, H.K., Noone, J.T.: Supporting special-purpose health care models via adaptive interfaces to the web. *Interacting with Computers* 14, 251–267 (2002)
38. Zajonc, R.: On the Primacy of Affect. *American Psychologist* 39, 117–124 (1984)