A Decision Theoretic Model for Stress Recognition and User Assistance

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Abstract

We present a general unified probabilistic decision-theoretic model based on Influence Diagrams for simultaneously modeling both user stress recognition and user assistance. Stress recognition is achieved through dynamic probabilistic inference from the available sensory data from multiple-modality sources. User assistance is automatically achieved by balancing the benefits of improving user performance and the costs of performing user assistance. In addition, a non-invasive real-time system is built to validate the proposed framework. Utilizing the evidences from four modalities (physical appearance features, physiological measures, user performance and behavioral data), the system can successfully recognize human stress and provide timely and appropriate assistance in a task-specific environment.

Introduction

Human stress is a state of tension that is created when a person responds to the demands and pressures that arise from daily life. Due to the adverse effects of excessive stress, it is important to monitor such an unhealthy state in a timely manner and treat it properly.

The causes and manifesting features of human stress have been extensively investigated in psychology, computer vision, physiology, behavioral science, ergonomics and human factor engineering. In spite of the findings from diverse disciplines, it is still a rather challenging task to develop a practical human stress monitoring and assistance system. First, the expression and symptoms of human stress are person-dependent and context dependent. Second, the sensory observations are often ambiguous, uncertain, and incomplete. Third, user's stress states are dynamic and evolve over time. Fourth, both stress recognition and user assistance must be accomplished in a timely and appropriate manner. Finally, lack of a clear criterion to access ground-truth stress creates additional difficulty in validating various stress recognition approaches and user assistance systems.

In this paper, we propose a general dynamic probabilistic decision-theoretic model based on Influence Diagrams (IDs) (Howard & Matheson 1984) to unify stress recognition with user assistance. Such a model yields several advantages. First, it provides a coherent and fully unified hierarchical probabilistic framework for representing and integrating the uncertainties embracing human stress modeling and user assistance determination at different levels of abstraction. Second, within the framework, the human stress detection is cast as a standard probabilistic inference procedure, while the user assistance is formulated as a decision-making procedure. Third, it naturally incorporates the evolution of human stress and accounts for the temporal aspect of decision making with the dynamic structure. Thus, such a model is an ideal candidate to accommodate the aforementioned challenges compared to other existing mathematical tools.

We intend to make two contributions. First, we provide a formal treatment of the theoretical foundations of stress recognition and automatic user assistance determination. Second, based on the framework, we develop a non-invasive real-time system that monitors human stress and provide user assistance in a task-specific laboratory environment. The system employs the evidences from four modalities: physical appearance, behavior, physiological measures, and performance. In addition, we adopt research results from psychological theories to validate the system. To the best of our knowledge, this is the first human stress detection and assistance system that combines the probabilistic approach with evidences from the four discrete modalities.

Related Work

Human stress has been studied in a number of diverse disciplines. Psychologists define emotions, and in particular stress, as valenced (positive or negative) reactions to situations consisting of events, actors, and objects (Ortony, Clore, & Collins 1988). Computer scientists find that facial expressions have a systematic, coherent, and meaningful structure that can be mapped to affective states (Beatty 1982; Breazeal 1999). Physiologists demonstrate that high stress level is accompanied with the symptoms of faster heart beat, rapid breathing, increased sweating, cool skin, feelings of nausea, tense muscles and alike. Ergonomic studies indicate the Inverted-U relationship exists between stress and performance of a task (Gardell 1982; Mindtools 2004).

Various approaches have been developed to recognize user stress. Physiological measures (EMG, ECG, respiration, and skin conductivity) are exploited to detect stress in a car driver (Healy & Picard 2000). A skin temperature measuring system is developed for non-contact stress evaluation in (Kataoka *et al.* 1998). In (Rani *et al.* 2002), the sympathetic and parasympathetic activities of the heart of a human are used to determine human stress level via wavelet decomposition and fuzzy logic techniques. (Rimini-Doering *et al.* 2001) combines several physiological signals and visual features (eye closure, head movement) to monitor driver drowsiness and stress in a driver simulator. The approaches or systems differ from each other in either the evidence modalities, or inference techniques, or both.

In addition to stress modeling, there is a rich collection of research on affective states recognition (Hudlicka 2003; Elliott, Rickel, & Friesen 1999; Kapoor, Picard, & Ivanov 2004). Especially in recent years, researchers have been increasingly interested in applying AI probabilistic representation and reasoning approaches to model user affect. The techniques are concerned with graphical models like HMM, Bayesian Network (BN) and Influence Diagram (ID). (Picard 1997) uses an HMM to model the transitions among three affective states: interest, joy and distress. HMMs, however, lack the capability of representing dependencies and semantices at different levels of abstraction for affect modeling. A dynamic BN is proposed in (Li & Ji 2004) to recognize user affect and provide user assistance. However, the user assistance function is triggered by some pre-determined thresholds since a BN does not possess an explicit representation for decision making (user assistance). (Conati 2002) proposes a dynamic decision network to monitor a user's emotions and engagement during the interaction with educational games. However, their work uses only bodily expression related features and also lack of validation.

Overall, our framework differs from the cited ones in that it employs the dynamic inference and sequential decision making techniques to unify stress recognition with user assistance, utilizes evidences from multiple modalities, and is validated in a real-time system with psychology theories.

A Dynamic Influence Diagram Model

Influence Diagram has been widely used as a knowledge representation model to facilitate decision-making and probabilistic inference under uncertainty. An ID contains random nodes, decision nodes, utility nodes and the links that characterize probabilistic relationships or time precedence between the nodes. A dynamic ID incorporates the evolution of random variables and accounts for sequential decision-makings with the temporal links between nodes. Figure 1 presents the dynamic ID for human stress modeling.

The diagram consists of two portions. The upper portion, from the top to "stress" node, depicts the elements that can alter human stress. These elements include the workload, the environmental context, specific character of the user such as his/her trait, and importance of the goal that he/she is pursuing. This portion is called *predictive portion*. On the other hand, the lower portion of the diagram, from the "stress" node to leaf nodes, depicts the observable features that reveal stress. These features include the quantifiable measures on the user's physical appearance, physiology, behaviors, and performance. This portion is called *diagnostic portion*. The hybrid structure enables the ID to combine the predictive factors and observable evidences in stress inference.

In the diagnostic portion, to model correlations among evidences from the same modality, an intermediate node is introduced for each type of evidence. For instance, a "physical" node is introduced to link "stress" and the observable visual features. The intuition is that the user stress influences his/her physical status; in turn, his/her physical status influences the observable features such as eyelid movement, head movement, facial expression and others. For the same reason, three other nodes "physiological", "behavior" and "performance" are added as well as their children nodes. These variables, represented as the intermediate nodes, are hidden. The bottom E_i nodes denote the observable evidences to reflect the states of their parents, e.g., E_1 can be the eye closure speed and blinking frequency, which are two evidences. The hierarchical structure in the diagnostic portion successfully integrates multiple-modality evidences.

In addition to modeling and recognizing human stress, another main function of this framework is to provide timely and appropriate assistances to relieve stress. Two types of decision nodes are embedded in the model to achieve this goal. The first type is the assistance node associated with the stress node. Assistance actions may have different degrees of intrusiveness to a user. For example, in one extreme, the assistance can be null if the user is at a decent stress level; in the other extreme, the user may be interrupted and forced to quit if he is in a very high stress level. How to design those assistances should depend on the applications. Another type of decision node is the sensory action node (S_i node in Figure 1). It controls whether to activate a sensor for collecting evidences.

Corresponding to the decision nodes, there are three types of utility nodes. The utility node (U_a) associated with the assistance node denotes the physical and interruption cost of performing that assistance. We would assign higher costs to assistances that require more resources and time, or interrupt user more. The utility node (U_{sa}) associated with both stress and assistance node indicates the benefit (penalty) of taking appropriate (inappropriate) assistance. For example, if a user is in a high stress level, the appropriate assistance may be to reduce workload level while the inappropriate assistance is to let the user continue his work or increase the workload. Thus the former should be assigned a high utility while the latter should be given a low negative utility. The utility node (U_i) associated with a sensory node denotes the cost of operating the sensor for evidence collection.

The temporal links in the ID capture the dynamics among variables and model sequential decision makings. The inter-slice arc from the stress at time t-1 to that at time t depicts how the stress self-evolves along time. More arcs can be added for the context, workload, trait and goal nodes because they may also change over time. We do not encode these arcs in the current model without loss of generality. The intra-slice arc from the assistance node at time t-1 to the stress at time t indicates the assistance applied in the previous step may change the stress level in the current step.

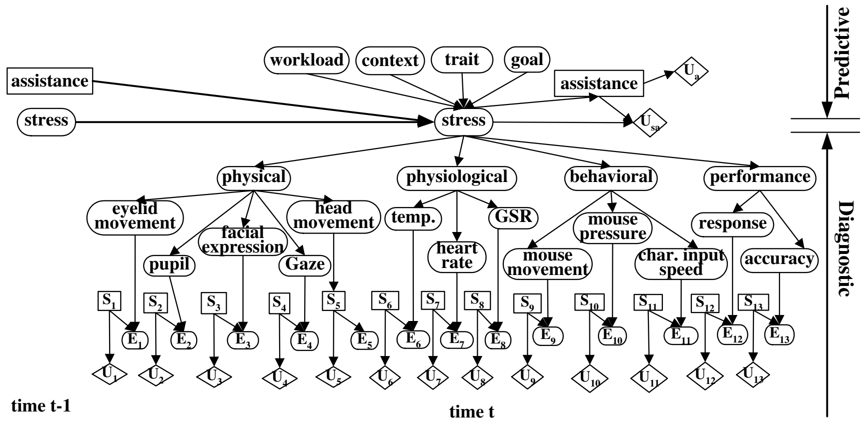


Figure 1: A dynamic Influence Diagram model for recognizing human stress and providing user assistance. For simplicity, we show the dynamic ID at time t but only draw the ”stress” and ”assistance” nodes at time t-1. Ellipses denote chance nodes, rectangles denote decision nodes, and diamonds denote utility nodes. Remark that there should be links from each S_i node to assistance node to indicate time precedence. And also a link from an assistance node at time t-1 to that at time t. We don’t draw it due to space limit.

Dynamic Stress Inference and User Assistance

Given the proposed dynamic ID, this section focuses on the techniques for recognizing affective states and determining user assistances.

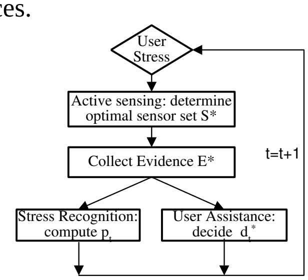


Figure 2: The flowchart for stress recognition and user assistance

Main Procedures

Figure 2 streamlines the main procedures in applying the dynamic ID to stress recognition and user assistance. At each time step t, the agent performs three procedures – active sensing, stress recognition, and user assistance. Specifically, the system decides an optimal sensory action set to collect evidences with an active sensing strategy. The collected evidences are then propagated through the model and the posterior probabilities of user stress p_t is computed with the dynamic inference technique. In the meanwhile, the system determines the optimal assistance $d_t^\star$ that maximizes the overall expected utility. After the assistance is performed, the user stress level may change and new evidences need to be collected. Thus the system goes to the next step and repeats the three procedures.

Stress Recognition

One function of the dynamic ID is to recognize user stress. The system estimates the user stress level at each time step t from the evidences collected from the selected sensors with the dynamic inference technique. We first introduce the notations and then define the problem. We shall use the first character of a node name to refer to the node, i.e. w referring to $workload$. In addition, we subscript a variable by a step t to refer to the variable at time t, i.e. s_t for stress node at time t. Under these notations, the ID model specifies two probabilistic relations: the stress transition model $p(s_t|s_{t-1}, w_t, c_t, t_t, g_t, d^*_{t-1})$ (d^*_{t-1} denotes the optimal assistance at time $t-1$) and the evidence generation model $p(z_t|s_t)$ where z_t is the set of evidences observed at step t. The inference at step t is to calculate the probability $p(s_t|z_{1:t}, d^*_{1:t-1})$ where $z_{1:t}$ is the set of all available evidences $z_{1:t} = \{z_k, k = 1, \ldots, t\}$ up to time t. In case $t = 0$, $p(s_t|z_{1:t})$ degenerates to the prior $p(s_0)$.

From a Bayesian point of view, the task is to recursively compute $p(s_t|z_{1:t}, d^*_{1:t-1})$ from $p(s_{t-1}|z_{1:t-1}, d^*_{1:t-2})$. The task can be accomplished at two stages: prediction using the predictive portion of the ID and correction using the diagnostic portion. In the prediction stage, the prior probability $p(s_t|z_{1:t-1}, d^*_{1:t-1})$ of user stress at step t is calculated by the Chapman-Kolmogorov equation:

$$\begin{aligned} & p(s_t|z_{1:t-1}, d^*_{1:t-1}) = \\ & \textstyle\sum_{s_{t-1}, w_t, c_t, t_t, g_t} p(w_t)p(c_t)p(t_t)p(g_t) \\ & p(s_{t-1}|z_{1:t-1}, d^*_{1:t-2})p(s_t|s_{t-1}, w_t, c_t, t_t, g_t, d^*_{t-1}) \end{aligned} \quad (1)$$

In the correction stage, the evidence set z_t is used to update the prior $p(s_t|z_{1:t-1}, d^*_{1:t-1})$ by Bayes’ rule:

$$\begin{aligned} p(s_t|z_{1:t}, d^*_{1:t-1}) &= \frac{p(z_t|s_t)p(s_t|z_{1:t-1}, d^*_{1:t-1})}{p(z_t|z_{1:t-1}, d^*_{1:t-1})} \\ &= \frac{p(z_t|s_t)p(s_t|z_{1:t-1}, d^*_{1:t-1})}{\sum_{s_t} p(z_t|s_t)p(s_t|z_{1:t-1}, d^*_{1:t-1})} \end{aligned} \quad (2)$$

User Assistance Determination

Another important function of the dynamic ID is to provide appropriate and timely user assistance. The ID combines probabilistic reasoning with utilities to decide the optimal assistance that maximizes the overall expected utility, which is defined as the optimal trade-off between the cost and benefit of the assistance. The cost of an assistance may include operational cost, interruption cost, and the cost of delaying or not providing the assistance. The benefit of an assistance is characterized by its potential to return the user to a decent stress level.

Given an assistance (decision) d, the expected utility EU_d can be computed as:

$$\begin{aligned} EU_{d_t} \quad &= \quad \textstyle\sum_s p(s_t|z_{1:t}, d^*_{1:t-1}) g_{U_{sa}}(s_t, d_t) \\ &+ g_{U_a}(d_t) + \textstyle\sum_i g_{U_i}(S_i) \end{aligned} \tag{3}$$

where the sum is taken over every possible value s of the stress state, g_U is the utility function of a utility node U. The quantity EU_d balances the benefit/cost of taking appropriate/inappropriate assistance (the first term), the operational cost (the second term) of performing assistance, and the operational cost (the third term) of using selected sensors.

The optimal assistance $d_t^\star$ is the one that maximizes EU_d among all available assistances.

$$d_t^* = \arg\max_d EU_{d_t} \tag{4}$$

Then $d_t^\star$ is applied to the user and may change his stress level probabilistically as specified in the model.

Model Implementation

We developed a real time human stress monitoring and assistance system to validate the proposed model.

Methodology

One fundamental difficulty in validating a stress monitoring system is lack of ground-truth stress. Some experiments have shown that even user self-reports are erroneous and unreliable. Fortunately, the existing results from psychological studies show that occupational stress is affected by two job characteristics: demand and control (Karasek 1979; Searle, Bright, & Bochner 1999). Demand refers to the amount of attention and effort required to carry out one's job. We will interchangeably use *demand* and *workload*. Control primarily refers to the decision-making freedom presented in a job. It is predicted and confirmed that a user becomes more stressful when workload is higher or when control is lower (Searle, Bright, & Bochner 1999). Thus in our system, we vary workload to change a subject's stress level. We will thus use workload to represent user stress level, instead of the (unavailable) ground-truth stress.

System Description

The system is shown in Figure 3. In experiments, a user sits in front of a computer screen and responds to the presented tasks. Three cameras are used to monitor user in real time, where one wide-angle camera focuses on the face and two narrow-angle cameras focus on the eyes. The captured videos are used to extract visual evidences. Meanwhile an emotional mouse is used to collect physiological evidences. The hardware specification can be found in (Ji, Zhu, & Lan 2004).

In order to alter user stress level, the environment is designed to be task-specific. The user is required to respond to asynchronously generated two types of tasks: a math task is about an addition/subtraction arithmetic of two two-digit integers, and an auditory 2-back task is to determine whether the current letter (t) is equal to or different from the letter that was two back (t - 2). Each experiment session consists of eight 10-minute blocks, where each block consists of sixteen intervals of 36s. In each block, the tasks are presented at the speed of 1s, 2s, or 4s. The workload is quantified as the number of tasks in an interval.

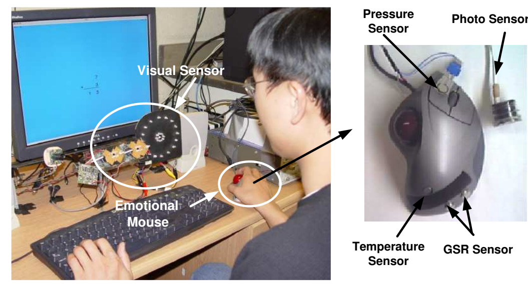


Figure 3: The real-time system

Three types of assistances are designed in the system. Type one is "no assistance", which means the system doesn't interrupt the user with any action. Type two is to decrease task presenting rate in an interval. And type three is to play music and display funny pictures in the screen, instead of presenting any tasks. From type one to type three, the intrusiveness to user increases.

Feature Extraction

We collected 16 measures under four categories. All these measures are obtained non-intrusively and in real-time. 8 measures are extracted from the real-time videos: Blinking Frequency (BF), Average Eye Closure Speed (AECS), Percentage of Saccadic Eye Movement (PerSac), Gaze Spatial Distribution (GazeDis), Percentage of Large Pupil Dilation (PerLPD), Pupil Ratio Variation (PRV), Head Movement (HeadMove), and Mouth Openness (MouthOpen). The detailed description of the visual extracting methods can be found in (Ji, Zhu, & Lan 2004).

In addition, the eMouse collects 3 physiological measures – heart rate, skin temperature and Galvanic skin response (GSR). For behavioral data, we monitor a user's interaction activities with the computer – the mouse pressure from fingers (MousePre) each time the user clicks the eMouse. For performance data, we collect math/audio error rate (MathErr, AudioErr) and math/audio response time (MathRes, AudioRes) which are extracted from a log-file that keeps track of user's responses to the tasks.

Experiment Results

The system has been tested with five subjects of different ages, genders and races. Each subject attends two experiment sessions (16 blocks, around 160 minutes). The data from one session is used for learning with the EM learning algorithm(Lauritzen 1995), while the data from another session is used for testing.

Stress versus Individual Measures

To study the relation between individual measures and stress, we carry out two types of well-known statistic techniques: ANOVA (Analysis of Variance) test and correlation analysis.

Measures	Subject A	Subject B	Subject C	Subject D	Subject E
HeartRate	.0001	.0026	.0040	.0041	.0026
GSR	.0019	.2289*	.0324	.1426*	.0089
MousePre	.0000	.0013	.0009	.0000	.3813*
AECS	.0062	.0001	.0557*	.0054	.0001
BF	.0000	.0000	.0070	.0368	.0036
GazeDis	.0000	.0036	.0723*	.0947*	.0002
PerSac	.0000	.0002	.0318	.0597*	.0204
PerLPD	.0000	.0204	.0747*	.0427	.0001
PRV	.0002	.0001	.0510*	.0162	.0163
MouthOpen	.0036	.0163	.1440*	.0114	.0594*
HeadMove	.0000	.0094	.1841*	.0959*	.0000
MathError	.0004	.0009	.0377	.0625*	.0000
MathResp	.0000	.0000	.0141	.4025*	.0000
AudioError	.0846*	.0918*	.3285*	.3319*	.0376
AudioResp	.1684*	.1979*	.0000	.0000	.0087

Table 1: Summary of sensitivity results with ANOVA test. The data denote the p-values. The values with * denote that the measure is not sensitive to stress changes for the corresponding subject.

ANOVA is used to determine if the means of each individual measure differ when the measure is grouped by different stress levels. In the test, the stress is divided into four levels. Table 1 displays the ANOVA test results for five subjects. The data in each cell indicates the p-value. If the p-value is less than 0.05, it is believed the test result is statistically significant, which means the measure is sensitive to stress. The table shows most measures are sensitive to stress. However, for different subjects, the same measure may have different degrees of sensitivity to stress. For example, AECS is sensitive to stress for subject A,B,D, and E, while it is insensitive for subject C. Also, some measures, e.g., AudioError, are almost not sensitive for all the subjects.

In correlation analysis, the correlation coefficients between each individual measure and stress are computed over time. It reveals how a measure varies as the stress undergoes changes. The coefficients demonstrate that most measures are closely correlated to the stress. As stress increases, a participant blinks less frequently, closes the eyes faster, dilates the pupils more often, focuses the eye gaze more on the screen, moves the head and opens the mouth less frequently, and clicks the mouse button harder. In the meantime, the heart rate increases, and GSR decreases.

Stress Recognition

To test whether the system can recognize user stress, in three test sessions, we purposely set the assistance as "null (no assistance)"; thus the subjects are not interrupted by the system. Figure 4 illustrates the results for three subjects, A, B, and C. In each chart, the solid curve denotes workload. As discussed earlier, we interpret workload as an indication of the external stress placed on the subjects. The dashed curve denotes the inferred stress levels. For subject A, the workloads are first gradually increased and then gradually decreased. The inferred stress shows the similar pattern. For subject B, the workloads are very high in the middle of the experimental period while they are low in the beginning and end. The inferred stress levels follow the similar trend. For subject C, the workload curve is more complicated. Basically, when the workloads are high(low), the inferred stress levels are also high(low). However, we notice that even though the workloads are same in the time period 1-18 and 41-48, the inferred stress levels are different, which may be explained by the "delay effect" caused by high workloads in the time period of 19-40. Overall, the experimental results suggest that our system can successfully monitor human stress in the task-specific environment.

Optimal Assistance

One primary function of the ID model is to provide timely and appropriate user assistance. Timely assistance means that the assistance is provided at time that the user is in an extreme stress level. Appropriate assistance optimizes the trade-off between the benefits of bringing the user to a decent stress level versus the costs of performing assistances and interrupting the user.

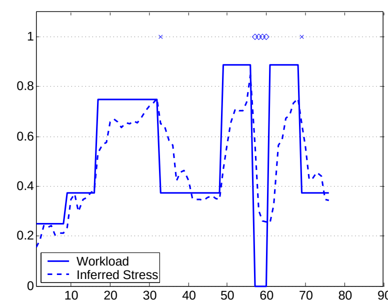
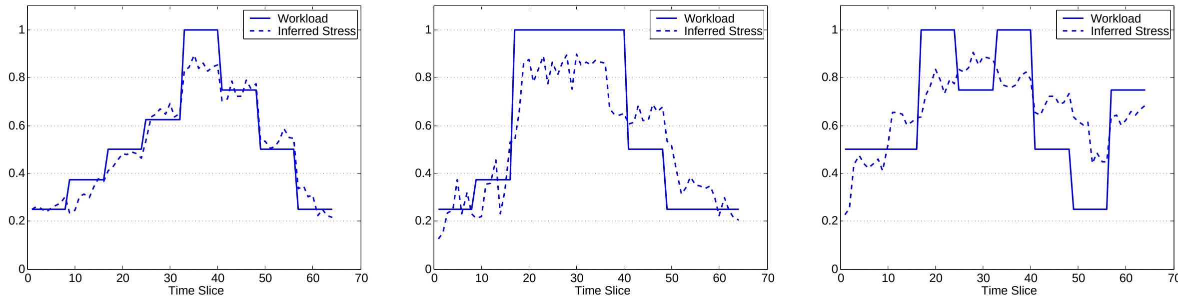


Figure 5: Timely and appropriate user assistance. Cross sign denotes type two assistance (decreasing task presenting speed); diamond sign denotes type three assistance (play music, etc); and default assistance is "no assistance".

Figure 5 shows the experimental result for subject D. The cross and diamond sign denote the assistance of type two and type three respectively. The default assistance is "no assistance". The fist assistance is taken around step 32, when the inferred stress level is around 0.75. This assistance is to decrease the task presenting speed. Thereafter, the user stress level decreases and maintains around 0.4. The second assistance is automatically taken around the time step 58, when the inferred stress level exceeds 0.8 due to the exterior high workload. The assistance is to play music and display funny pictures in the screen, thus the workload is zero during the time period of 57-60. With this assistance, the inferred stress level drops to around 0.3. The third assistance is taken around the time step 70, when the stress level goes up again to above 0.7. After the assistance, the stress level drops to around 0.4 again. In summary, since the system can automatically provide timely and appropriate assistances, the user stress levels don't go to very high and thus the user is able to maintain in a positive state. On the contrary, in Figure 4, the user stress level can be as high as 0.9 since no assistance is provided.



(a) (b) (c)

Figure 4: Inferred stress level versus workload: (a) subject A, (b) subject B, and (c) subject C. Each time slice denotes an interval of 36 seconds. The solid curve denotes workload, whose values are normalized to the range of [0 1] while the dashed curve denotes the inferred stress. We interpret workload as an indication of the external stress placed on the subjects, regarded as "ground-truth" stress.

Conclusion and Future Work

We presented a dynamic ID framework for achieving two goals: (1) stress recognition by dynamic probabilistic inference given the multi-modality evidences including physical appearance features, physiological measures, user performance and observed behaviors, and (2) automated user assistance by balancing the benefits of improving user productivity and the costs of performing possible user assistances. We built a real-time human stress monitoring and assistance system to validate the model correctness and effectiveness. The experiments show that this system can successfully recognize human stress and provide timely and efficient assistances. Our future work is to extend the current framework to affective state recognition in addition to stress modelling.

Acknowledgments

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