Using Mental Load for Managing Interruptions In Physiologically Attentive User Interfaces

Daniel Chen and Roel Vertegaal
Human Media Lab
Queen's University, Kingston, Ontario
{chend,roel}@cs.queensu.ca

ABSTRACT
Today's user is surrounded by mobile appliances that continuously disrupt his activities through instant message, email and phone call notifications. In this paper, we present a system that regulates notifications by such devices dynamically on the basis of direct measures of the user's mental load. We discuss a prototype Physiologically Attentive User Interface (PAUI) that measures mental load using Heart Rate Variability (HRV) signals, and motor activity using electroencephalogram (EEG) analysis. The PAUI uses this information to distinguish between 4 attentional states of the user: at rest, moving, thinking and busy. We discuss an example PAUI application in the automated regulation of notifications in a mobile cell phone appliance.

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Attentive user interfaces, Brain-Computer Interfaces

ACM Classification Keywords
H5.2 Information Interfaces and Presentation User Interfaces: Input devices and strategies

INTRODUCTION
Today's computer users typically employ multiple mobile computing devices, such as PDAs and cell phones, to provide them with wireless communications throughout their everyday environment. Although we are now using multiple appliances, each appliance's design is still based on the premise of it being the user's only device. Consequently, when initiating communications with the user appliances act in isolation. This leads to multiple and simultaneous interruptions that are insensitive to the user's workload or context. Mobile devices may interrupt meetings and conversations, and email notifications may disrupt workflow and focused activity. We believe that a system that regulates communications activities among devices will reduce such demands on the user's mental load.

The Attentive User Interface (AUI) paradigm [16] tries to address this problem by allowing devices to actively allocate attentive resources of users and systems in a way that optimizes user focus. AUI interaction techniques allow the interface to adapt dynamically with the user's attentional state by measuring user attention for devices and tasks. Before notifying the user, AUIs reason about the importance of their message relative to the user's current activity [4]. In order to determine user activity, today's AUIs rely on two methods. Firstly, they measure overt characteristics of user attention, for example, through eye tracking devices [1]. This allows AUIs to determine what device the user is currently engaged with [14]. Secondly, AUIs construct Bayesian models of user behavior by collecting data throughout interactions with applications [3]. Unfortunately, neither approach provides adequate information about the actual engagement of a user. While eye tracking devices or eye contact sensors may tell which device the user looks at, they can not distinguish whether the user is simply looking at the device, or actually engaged in focused activity with it.

In this paper, we explore techniques that allow AUIs to gather direct information on the mental engagement of the user through physiological measures. We discuss a prototype Physiologically Attentive User Interface, or PAUI, a novel attentive user interface that regulates user mental load dynamically by automatically distinguishing attentional states. We discuss an example PAUI application in the automated regulation of cell phone notifications on the basis of classification of attentional state using motor activity and heart beat irregularity measures.

PREVIOUS WORK
Early work applying physiological signals to user interfaces relied typically on the use of uni-modal measures. McCraty et al. [6] showed that specific emotions could be distinguished based upon the power spectrum of the *electrocardiogram* (ECG) measured from the heart. According to McCraty, in cases of stress, there is a tendency for increased heart-rate variability (HRV) in the lower frequency ranges (< 0.1 Hz) of the ECG. Emotional states such as appreciation exhibit high power in the medium frequency ranges (~ 0.1 Hz). Rowe et al. demonstrated that stress measures provided by ECG low frequency components correlate well with mental load of users during complex visual tasks [11], as measured by the

NASA TLX subjective workload assessment tool [7]. Researchers have also long explored the use of *electroencephalograms* (EEG) for input, correlating it with various neurological processes. Trejo et al. developed fine grained control of an aircraft joystick using EEG motor activity measures [2]. In HI-Cam [5], EEG motor activity measures were used to control the brightness of wearable computer displays. Although EEG provides a valuable measure, its uni-modal application suffers from noise. When combined with other physiological signals, such as ECG, skin conductance, blood pressure, muscle tension and respiration, recognition rates can be improved. By combining analysis of galvanic skin response and electromyogram (EMG) signals, Picard and Healy were able to robustly classify user emotional states such as anger and grief [8]. However, there has been little use of real-time physiological measures towards interfaces that dynamically manage the user's mental load. Prinzel et al. used EEG motor signals to determine alternation between automatic and manual modes of a task [9]. We have built upon this work, combining ECG and EEG activity measures to predict the user's interruptability in a mobile setting.

PHYSIOLOGICAL MODELING OF ATTENTION: HEART AND MIND

Both the heart and the brain provide signals that allow probabilistic modeling of user load and activity [12, 13]. In order to estimate user engagement, we explored measures of the heart's electrocardiogram (ECG) and the brain's electroencephalogram (EEG) signals. The heart's electrical potential produces an electromagnetic field 5000 times stronger than the brain. The heart emits the highest electrical activity in all the body's organs, providing robust physiological data about the user's load levels that might be more difficult to detect via EEG alone. While ECG provides information on mental load, EEG allows a robust identification of motor-related activity. Combining these two sources allowed us to create more accurate models of the user's attentional state.

ECG-based Models of Attention Using HRV Stress Analysis

The ECG signal is regulated by both the sympathetic (SNS) and parasympathetic nervous system (PNS). Biochemical messages sent from the brain use both the SNS and PNS to regulate the heart and other organs in different situations. The SNS acts to increase the heart rate when high stress levels are experienced, eliciting what is known as the "flight or fight" response in situations of anger, frustration, or agitation. Typically, however, the PNS counters the effect of the SNS by decreasing the heart rate. It is the PNS that regulates our heart in normal situations, where we are not under high stress. Our system analyzes the ECG signal in the following way. Heart rate is typically defined in beats per minute, calculated by the time interval between the highest peaks of the heart wave. The heart rate variability (HRV) is calculated using the standard deviation of the heart rate data. User state is then determined using spectral analysis of the HRV signal. Mental load estimates are obtained through low-pass filtering of HRV spectral components, measuring low frequency (LF) power in the region below 0.1Hz.

	Low Motor Activity (EEG)	**High Motor Activity (EEG)**
Low LF Power (ECG)	*User State 1* -Low mental activity -At rest *Candidate Activities* Pausing, Relaxation.	*User State 2* -Low mental activity -Sustained movement *Candidate Activities* Moving.
High LF Power (ECG)	*User State 3* -High mental load -At rest *Candidate Activities* Driving, Reading, Thinking	*User State 4* - High mental load - Sustained movement *Candidate Activities* Meeting, Lecturing, Writing

Table 1. Classifying activities according to attentional state.

EEG Based Model of Attention using Frequency Spectrum Analysis

Our system uses EEG to further disambiguate user state. EEG, although smaller in electrical potential than the ECG, provides valuable information on motor-related attention. Motor activity is detected through spectral analysis of the EEG signal. Prior studies have shown that the use of a single electrode is sufficient to gather motor-related information from the EEG signal [5]. Our system measures the EEG's event-related desynchronization in the Mu-power range [10], with a frequency range from 8 to 30 Hz. Just before and during the onset of a motor-related activity, a decrease in power can be observed in this signal. We deployed this measure to distinguish between two states of motor activity by the user, *at rest* and *performing a motor-related task*.

PAUI CLASSIFIER: CLASSIFYING STATES AND DEGREES OF ATTENTION

PAUIs may distinguish between various degrees of attentional states by combining multiple physiological signals. The LF spectral components of ECG provide indicators for mental activity, but do not necessarily indicate action. By combining HRV information with EEG motor activity signals, PAUIs determine whether the user is actively partaking in a task, or more passively engaged. Although we do not focus on this in the present paper, we may further disambiguate the user's activity using information from sensors in the user's environment [3].

Table 1 shows the ECG and EEG based classifiers used for modeling the user's attentional state. We distinguish four user states that aid in predicting the availability of users for interruption. Under this scheme, the lowest degree of

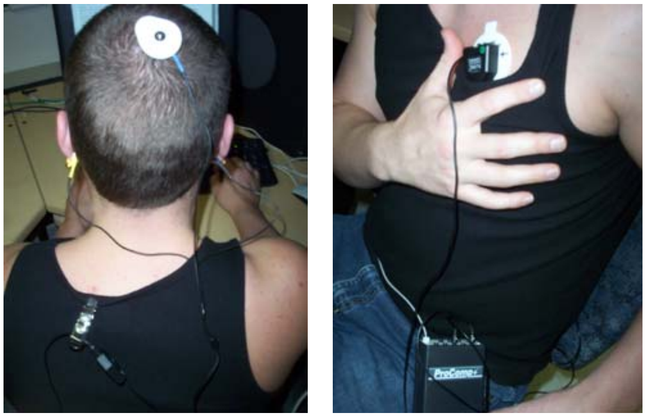

Figure 1. EEG sensors (left) provide information on the user's motor activity, while ECG sensors (center) provide information on the user’s mental load.

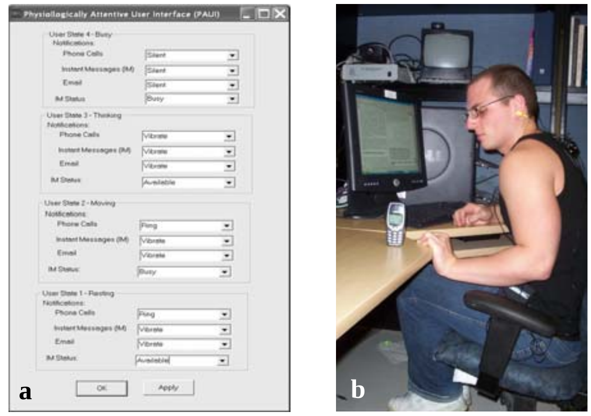

Figure 2 a) The PAUI preference panel allows users to set notifications per user state and per medium. Fig. 2 b) User responding to a PAUI phone interruption.

attention is exhibited in state 1, where the user is not actively engaged in a task. In a work context, this state typically may be interpreted as having the lowest possible cost of interruption. This observation, however, cannot be generalized to other contexts, where a state of relaxation may in fact represent a high cost of interruption. Our next user state is typical for users in transit, for example, when moving to an appointment. This state typically provides a low cost of interruption for speech-related interruptions such as cell phone calls, but a higher cost of interruption for activities that require the motor system to be engaged in the response, as is the case for instant messaging and email. The third user state is indicative of mental occupation while at rest, such as when reading, driving or thinking. Users in this state may wish to be notified of communications, but not through auditory means, as this would potentially interfere with mental engagement. Finally, user state 4 indicates active involvement in an activity that places severe constraints on available mental resources, and thus a high cost of interruption. In this state, we may wish to either defer notification, or communicate a busy state.

APPLICATION: THE PAUI CELL PHONE

We augmented a standard Nokia cell phone with capabilities for detecting user state as per the above classification. We based our prototype on the existing Attentive Cellphone design [17]. The Attentive Cellphone used an eye contact sensor and speech analysis to detect whether its user is in a face-to-face conversation. It used this information to inform callers whether the user was busy, through an automated instant messaging status indicator associated with each contact. Rather than having the system decide whether or not to allow the call through, this allowed callers themselves to decide the cost of interrupting the user with their message. Instead, our PAUI phone regulates the notification level automatically depending on user preferences set for each attentional state (see Figure 2a). The phone has three optional notification levels for each communication medium: ring, vibrate, or silent mode.

Preferences may be different for each communication medium, allowing users to differentiate the cost of interruption for email, IM and phone calls. The following is an overview of a typical user preference.

- *State 4.* Set phone call notification to silent mode. Set IM status to busy. Set email and IM notification to silent mode.
- *State 3.* Set all notifications to vibrate. Set IM state to available.
- *State 2.* Set phone call notification to ring. Set IM status to busy. Set email and IM notification to vibrate.
- *State 1.* Set phone call notification to ring. Set IM status to available. Set email and IM notification to vibrate.

Additionally, the phone supports the use of different ring tones for different communication media, and the identification of caller groups through ring tones.

Hardware Setup

The PAUI set up consists of three sets of components. Firstly, a wearable Procomp+ system by Thought Technology [15] is used to acquire continuous real-time physiological data. The ProComp+ samples EEG and ECG data at 256 samples/sec, sufficient for robust power analysis. The second component is the PAUI filtering software, which runs on a wearable computing platform running at 800 MHz. After initial calibration of thresholds, the filtering software determines user state via a straightforward binary classification. The third component consists of any standard Bluetooth cellphone. The wearable system is notified of incoming calls on the cellphone through a virtual com port connection over Bluetooth. AT modem commands are then issued, allowing the wearable to produce the appropriate notification by playing a particular ring, or by activating the cell phone’s vibration unit. User preferences for notifications are set directly on the wearable system through a standard GUI (see Figure 2a).

Usage Scenarios

In our first scenario, the PAUI phone automatically regulates all notifications. However, there are situations in which a user may want case-by-case control over interruptions. We are currently exploring the use of our PAUI architecture for detecting transitions between user states, deploying these to remotely operate the PAUI phone. Transitions upon notification from a higher attentional state to a lower attentional state and back have been successfully deployed to suppress individual notifications.

The following scenarios illustrate the process. User David is busy writing a particularly complicated section of an essay. The PAUI phone detects the high mental load and motor activity and classifies it as a state 4. In our first scenario, the phone automatically suppresses all notifications for incoming calls. In our second scenario, the system notifies the user of each incoming phone call with a ring, interpreting a subsequent shift in attentional state as a response to the notification. User David hears the ring, and is briefly distracted upon notification (see Fig 2b). This is detected by the system as a shift to a lower attentional state. David then continues work without picking up the phone. Upon detection of the transition back to state 4, the PAUI automatically silences the notification, causing the interruption to be withdrawn.

Evaluations

Initial evaluations of the above approaches to interruption management are encouraging. During a 6-person trial, our first prototype identified the appropriate notification level in 83% of cases. Results regarding the direct control of notifications through attentional shift detection are, however, still preliminary.

CONCLUSIONS

In this paper, we presented Physiologically Attentive User Interfaces, or PAUI, which allow user interfaces to regulate notifications by devices through measures of the user's mental load. We discussed a prototype that measures mental load using Heart Rate Variability (HRV) signals, and motor activity using electroencephalogram (EEG) analysis. The PAUI architecture uses this information to distinguish between 4 attentional states of the user: at rest, moving, thinking and busy. We applied this in the automated regulation of notifications in a mobile cell phone appliance.

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