Towards a Physiological Model of User Interruptability

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Abstract. User interruptability has become an important topic of study in Human-Computer Interaction (HCI). However, automatically determining the availability of users is still problematic. In this paper, we present a preliminary study of the use of physiological measurements for predicting user interruptability status. We measured Heart Rate Variability (HRV) and Electromyogram (EMG) signals whilst users performed a variety of tasks; including reading, solving word puzzles, mental arithmetic, typing, and playing a racing game. Results show high correlations for both HRV (r = 0.96) and EMG (r = 0.85) with user self-reports of interruptability. We combined these two measures into a single linear model, which predicted user interruptability with a combined r^2 of 0.95, or 95% of the variance. Please note that our model, at this stage, describes interruptability across users rather than per individual. We describe an application of our findings in the Physiological Weblog, or 'Plog, a system that uses our model for automating online messaging status.

Keywords: Interruptions, Blogs, Attentive User Interfaces (AUIs).

1 Introduction

With the emergence of camera phones and other mobile imaging devices, many users are capturing their daily lives and posting them online [4]. One example of this recent trend is the mobile blog, or 'moblog [18], a wearable form of blogging. Another example is the movement towards continuous capture or archival of personal experience [2], for example, using video glasses like eyeTap [21] or eyeBlog [6] (see Figure 1).

With the availability of ubiquitous wireless devices, we have also seen an increase in communications between users. However, since these devices are not aware of the status or availability of their user, they often interrupt the user's tasks and thought processes at inopportune times [12]. Studies have shown that workplace interruptions via communication devices adversely affect productivity and lower worker performance [17, 23].

The Attentive User Interface (AUI) paradigm [29] attempts to address these challenges by allowing devices to allocate the attention that users have for their tasks and devices in a more optimal fashion. According to Shell et al. [29], AUIs achieve this through 1) sensing, 2) reasoning about, and 3) augmenting user attention. However, little research has been done on how AUIs might communicate attention to signal availability of others for online communications.

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Fig. 1. Continuous archival of personal experiences using eyeBlog video glasses [6]

This paper extends work on the Physiologically Attentive User Interface (PAUI) [5], and presents a study on the use of physiological measures for automated detection of user interruptability. We discuss an application of our findings in the Physiological Weblog interface, or 'Plog for short. Like PAUI, this system allows online users to assess availability of mobile users through a web-based interface. We first discuss background literature on interruptability and the use of physiological measures in HCI. We then discuss our experiment, and conclude with a description of the 'Plog system.

2 Previous Work

There is very little work on the combination of blogging technologies and physiological interfaces. Since work on personal blogging tools is extensive, we restrict our discussion to studies involving interruptability. This section discusses previous work on interruptability, and the use of physiological measures in Human-Computer Interaction.

2.1 Interruptability

There has been a considerable interest in the modeling of user activity for the purpose of determining availability for notifications and communications [1, 3]. Horvitz et al. [13, 15] approached this problem using Bayesian reasoning models that allowed prediction of user interruptability on the basis of a variety of measures of interactive behaviors. They created attention-based models based upon analysis of keyboard and mouse events during interactions with applications such as, for example, Microsoft Outlook. Horvitz et al. also measured the effect of interruptions by calculating the cost of interruption, from user feedback on video recordings [14]. The cost of interruption varied according to the state of the user, with highly focused tasks obtaining a higher cost of interruption. In this way, attention-based states like driving and sleeping could be detected and correlated with a particular cost of interruption. Horvitz et al. [16] applied their Bayesian reasoning models in the Lumière project, which was used to provide automated assistance in popular software applications.

Hudson et al. [17] used a "Wizard of Oz" study in an office setting to gather attention-based data from video-recorded user interactions. They used a "beeper" approach to poll users for their current interruptability, rated on a linear scale. Like Horvitz, they were able to uncover correlations and build statistical models for the prediction of human interruptability based upon overt physical activities [10].

In [30], Siewiorek et al. presented SenSay, a context-aware mobile phone that sensed physical and environmental changes in order to determine current user interruptability. SenSay determined if a user was in a busy (uninterruptable) state based upon their electronic schedule, their movement, and any audible noise in the environment. However, the device was limited due to its reliance on external measures in the user's surroundings, which are not always related to interruptability.

2.2 Physiological Measures

Some of the earliest research that combined Human-Computer Interaction with physiology was by Picard et al. [25]. They used physiological sensors to analyse facial muscle tension, blood volume pulse, skin conductance, and respiration rate. After several weeks of data collection from one participant, they were able to create a feature-based algorithm using Sequential Floating Forward Search with Fisher Projection (SFFS-FP) [26] that was 81% accurate in the classification of eight emotional states (including anger, joy, and grief).

Our paper draws inspiration from this work, with the hopes of modeling interruptability by measuring physical and mental activity of the user without having to overtly identify specific user tasks. In taking this approach, we hope to correlate the user's physiological responses to their self-assessed interruptability, thereby creating a task-independent model of interruptability based purely on the user's current physiological state.

Determining Mental Load. To obtain a model, we first needed to determine which measures would most likely correlate with user interruptability. As a first candidate, we examined measures of user mental load during a task. In the past, the most common measure of mental load has been NASA's Task Load Index (TLX) [11], a subjective self-assessment of various mental and physical aspects of a task. Results take the form of a multi-dimensional rating, based on the weighted average of six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration.

Later, Rowe et al. [28] released a preliminary study indicating that mental effort may be reflected in Heart Rate Variability (HRV) [22]. In their experiment, participants' HRV was monitored whilst playing air traffic control games with varying levels of difficulty. After completing the task, participants were asked to fill out the NASA TLX Test for Mental Effort. Results from the TLX showed significant increases in mental load with task difficulty. HRV correlated well with measures from the TLX questionnaire, with the advantages that HRV can be determined in real time; and is an objective measure, not reliant on participants' self-assessment. We therefore decided to use HRV as our physiological indictor of mental load.

The Parasympathetic and Sympathetic Nervous Systems. Within the human nervous system there are two opposing systems at work: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS prepares the body for potentially dangerous or stressful situations by increasing both heart rate and blood pressure. Conversely, the PNS is the calming force that returns the body to normal after stimulation by decreasing heart rate and blood pressure. The balance between these two opposing forces is known as the sympathovagal balance, and it is these changes in the cardiac cycle that are reflected in Heart Rate Variability (HRV) measure [20].

Determining Physical Activity. To complement measures of mental activity, we also examined ways in which we could measure physical activity. In the past, electroencephalogram (EEG) was typically used to measure gross motor movement using *mu*-related desynchronisation [27]. This approach has been used in work by Chen and Vertegaal [5] on Physiologically Attentive User Interfaces. However, EEG can be quite invasive because it requires direct scalp contact and the use of electrolytic gels.

Instead, we chose to use electromyography (EMG), a direct measure of muscle activity. EMG is much less invasive than EEG, as it only requires the placement of one dry sensor on the muscle in question. This has the advantage that it can be used to measure signals throughout the user's body for detecting specific muscle contractions. In order to minimise the intrusiveness of data acquisition we decided to examine the use of EMG for our interruptability model.

3 Obtaining HRV and EMG Measurements

We will now discuss how measurements of both Heart Rate Variability and Electromyography were obtained and analysed for use in our model.

3.1 HRV: Analysing the ECG Signal

Measures of Heart Rate Variability (HRV) are obtained through the analysis of Electrocardiogram (ECG) signals [8]. A typical ECG signal is shown in Figure 2, with each peak consisting of a complex pattern of pulses labeled *PQRST*, as illustrated in Figure 3. The most recognisable feature is the *R* peak, which represents the point in time where the ventricles of the heart are completely depolarised. We used the time interval between subsequent *R* peaks in determining both the heart rate itself and Heart Rate Variability.

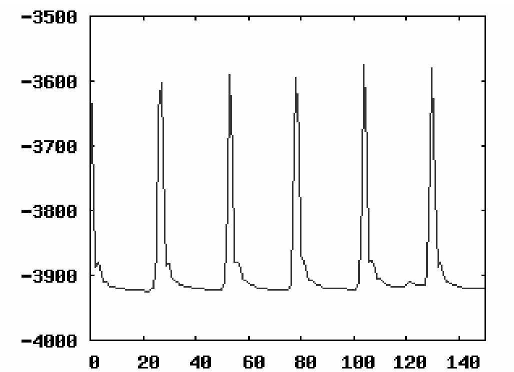

Fig. 2. Electrocardiogram (ECG) signal

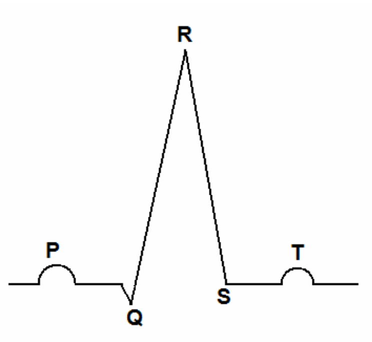

Fig. 3. PQRST structure

A number of feature variables were used to explore how physiological signals correlated with interruptability (see [32] for a more detailed discussion):

1) ECG Heart Rate Variability (Time Series): This measure is found by taking the standard deviation of the time interval between R peaks.
2) ECG Heart Rate Variability (Frequency Domain): Here, measures of HRV are taken in the frequency domain. First, we take the Fourier transform of the R-R peak interval series, known as the tachogram. We then measure the resulting power in the 0.1Hz range, which has been shown to vary with mental load [28].
3) ECG RMSSD (Root Mean Square of Successive Differences): This measure is calculated by finding the square root of the mean squared differences between successive R-R peaks.
4) ECG Beats Per Minute: This is the heart rate itself, as defined by the time interval between successive R peaks; and is used as an indicator of physical activity.

3.2 Analysing the EMG Signal

The typical EMG signal is irregular in comparison to the ECG signal, extracting usable signals is therefore more difficult. The signal is a flat line prior to muscle contraction, then peaks with contraction, after which it becomes somewhat erratic.

The following feature variables were used to determine EMG activity:

1) EMG Count (Small and Large): Given a window of EMG data, this variable is incremented when a data point lies above a threshold. The use of small or large thresholds allows distinction of smaller versus larger muscle contractions.
2) EMG Standard Deviation (EMGSD): Given a window of EMG data, this variable takes the standard deviation of the EMG measurement. As the signal increases in contraction, the amount of variation and deviation from the mean will also increase.
3) EMG Power: Given a window of EMG data, this measures the overall power of the signal.

An advantage of the latter two EMG feature variables is that they do not require calibration, whereas the EMG Count variable requires visual inspection so that meaningful threshold values can be chosen.

4 Evaluation

To obtain a generalised physiological model of interruptability, we designed a preliminary experiment that related participants' self-perceived interruptability to their physiological state as measured by Heart Rate Variability (HRV) and muscle activity (EMG). We used a beeper-study approach similar to that used by Hudson [17], asking participants to verbally state their interruptability whilst performing five different tasks with varying levels of both mental difficulty and physical activity.

4.1 Participants and Design

A total of nine people participated in our experiment. Participants consisted of six males and three females with a mean age of 24.3 years; all were regular computer users. We employed a within-subjects design, meaning that all nine participants performed all five tasks. The order of presentation was counterbalanced between subjects to eliminate any bias due to ordering.

4.2 Apparatus

A wearable Procomp+ system by Thought Technology [35] was used to continuously acquire discrete real-time physiological data from four sensors placed on the participant's body. Each sensor consisted of three silver chloride electrodes in a triangular formation, with a spacing of 2cm between electrodes.

The ProComp+ system samples both ECG and EMG at 32 samples per second, which is sufficient for both HRV and EMG power analysis. Our software logged the physiological data with a time stamp for offline analysis. The computer system used a 2.0 GHz Pentium 4 processor, running a Debian Linux operating system.

4.3 Sensor Placement

We affixed four adhesive sensors to each participant (see Figure 4). One sensor was placed on the left side of the upper chest to measure HRV, while the other three sensors were used to measure EMG in the upper fibres of the trapezius in the right shoulder, the extensor carpi radialis in the right forearm, and the tibialis anterior in the lower right leg.

4.4 Task Description

Participants were first briefed about the experiment, and familiarised with each of the five tasks. The experimenter told participants that they would be interrupted every 30 seconds and asked to verbally state their interruptability. Participants were told to

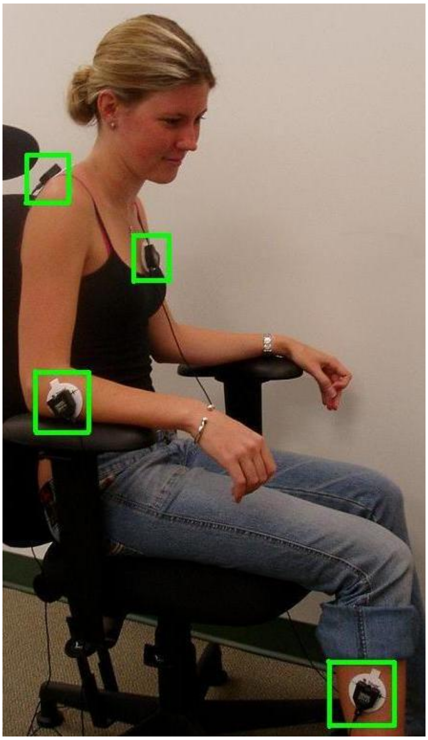

Fig. 4. Sensor placement

Fig. 5. Participant performing the racing game task

answer on a scale of one to five, with one meaning “I am completely available for interruptions”, and five meaning “I do not wish to be interrupted”. Each task took approximately three minutes to complete, and we therefore collected roughly 15 minutes of data for each participant. Participants remained seated during all five conditions.

4.5 Task Conditions

We selected the following five tasks, which varied in both mental difficulty and physical activity:

- *Reading*
  Participants were presented with a short reading passage of approximately 1100 words (taken from [9]). In order to encourage more thorough reading, participants were forewarned that they would be tested regarding the passage’s contents through a multiple-choice comprehension test with 10 questions. Physiological data was logged for the duration of the reading period, but not whilst the subjects were answering the questions.

- *Mental Arithmetic*
  The experimenter read 30 simple mental arithmetic questions to the participant. The questions were in the form "9 – 4 + 2", and were designed such that all of the answers fell between one and nine. Participants were required to answer verbally, and as quickly as possible.

- *Typing*
  Participants were presented with a web-based typing speed test [33]. For fair comparison, all participants were required to type the same passage (an excerpt from "The Adventures of Huckleberry Finn" [36]). Participants were allowed to practice prior to the task.

- *Word Puzzle*
  We chose an online anagram puzzle called Text Twist® [34], where the user is presented with a number of scrambled letters. The task is to rearrange the letters in order to create as many words as possible. Participants were given three minutes to find as many permutations as possible.

- *Racing Game*
  Participants played a racing game on an XBOX console [24] connected to a 42" widescreen plasma display (see Figure 5). We chose the game "Need For Speed Underground 2" [7], as it provides a high-resolution simulation of a driving task. To provide participants with a more realistic experience we used a Madcatz MC2 [19] steering wheel and surround sound stereo equipment. All participants were allowed to practice prior to the task. All participants used the same car model, and drove the same course, with no opponents or traffic.

4.6 Hypothesis

We hypothesise that both HRV and EMG measures correlate with participants' self-perceived level of interruptability, as these measures predict both mental effort and physical exertion during a task.

5 Results

In order to achieve the most accurate results, we analysed all four HRV feature variables (see Section 3.1) and all three EMG feature variables (see Sections 3.2). We chose to use the standard deviation of Heart Rate Variability (Time Series) as our mental load metric and the standard deviation of EMG (EMGSD) as our muscle activity metric, as these measures proved to be the most consistent.

Figures 6 and 7 shows the relationship between the self-assessed interruptability and our mean measures for HRV and EMG respectively, averaged over all five tasks. Since both the HRV and EMG are measured in standard deviations, the y-axes of the graphs are unitless. As we expected, linear regressions showed a significant correlation of HRV with interruptability scores of $r = 0.96$ ($p < 0.01$). EMG measures also showed a significant correlation of $r = 0.85$ ($p = 0.03$).

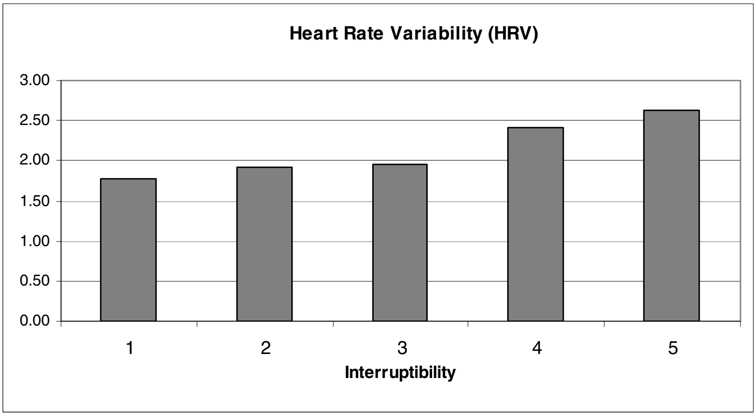

Fig. 6. Mean HRV levels with self-perceived interruptability

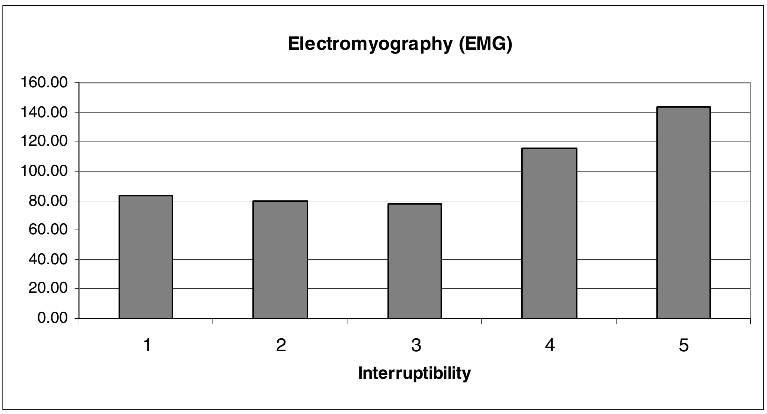

Fig. 7. Mean EMGSD levels with self-perceived interruptability

We combined the two measures into a single model, as follows:

$$Interruptability = a + b\ (HRV) + c\ (EMGSD) \tag{1}$$

Multiple regression showed an excellent fit to the model, with $r = 0.98$ ($r^2 = 0.95$) and the following results for our constants *a, b* and *c:*

$$Interruptability = -8.12 + 6.89\ HRV - 0.04\ EMGSD \tag{2}$$

6 Discussion

Results show that, as expected, both measures of HRV (Time Series) and EMGSD increased significantly with participants' self-perceived interruptability level.

Surprisingly, our model predicts up to 95% of the variance in interruptability scores, across a variety of tasks. This is a very high correlation indeed. Although such results may in part be attributable to an averaging effect of the linear regression across participants, we must note that analysis of individual correlations is problematic. The random variable nature of the beeper study method cannot ensure every subject reports on the entire range of interruptability scores from one to five at all times. This makes pooling of results essential, and averaging of individual correlations impractical.

However, our results should not be interpreted to predict interruptability for any *specific* individuals, which is what our applications would require, but rather as a clear indication of the value of HRV as a means for measuring interruptability of groups of individuals in an automated fashion. We believe such results are extremely promising, and warrant further longitudinal investigation with larger sample sizes. One potential concern regarding the beeper method is that the act of interrupting the user to ask their interruptability may itself affect the resulting measurement. However, our results make this unlikely, and indicate a significant variance in interruptability scores throughout the various tasks. Another potential concern may be the relatively low sampling rate of our Procomp+ system. Again, our regression results show that relatively low-cost and potentially wearable measurement equipment may generate significant predictive power, which is a requirement for our applications. We also note that results may not necessarily apply to task situations where the user's heart rate is particularly elevated, such as during exercise.

Mental load appeared to contribute more to our model than muscle activity, as the HRV coefficient (6.89) was much greater than the EMGSD coefficient (0.04). While the model is improved by the inclusion of EMG data, we believe measures of mental load provide a more reliable estimate of interruptability. Our results are largely in line with prior experiments [28].

Our research suggests that it may be possible to correlate the internal physiological state of the user with their self-reported level of interruptability without the need to identify or classify the specific task that the user is currently involved in.

7 'Plog: A Physiological Weblog

We applied our findings in 'Plog, an automated availability status system that blogs the user's physiological state, as well as their predicted interruptability (see Figure 8). The most important function of 'Plog is the *communication* of attention, thus allowing for an alternative approach to regulating interruptions. Note that because 'Plog relies on other users to interpret the recipients' states, a high degree of individual predictive power is not absolutely critical. In part, we believe 'Plog works by making others more aware of the need to be more considerate of recipients' interruptability.

'Plog continuously uploads physiological data information to a web server through a secure *ssh* protocol [31]. The system is tailored to each user's individual physiological signals, and uses both HRV and EMG to infer the user's current level of interruptability. This information is represented using a simple interface that displays the interruptability on a scale from one to five. This allows people to maintain

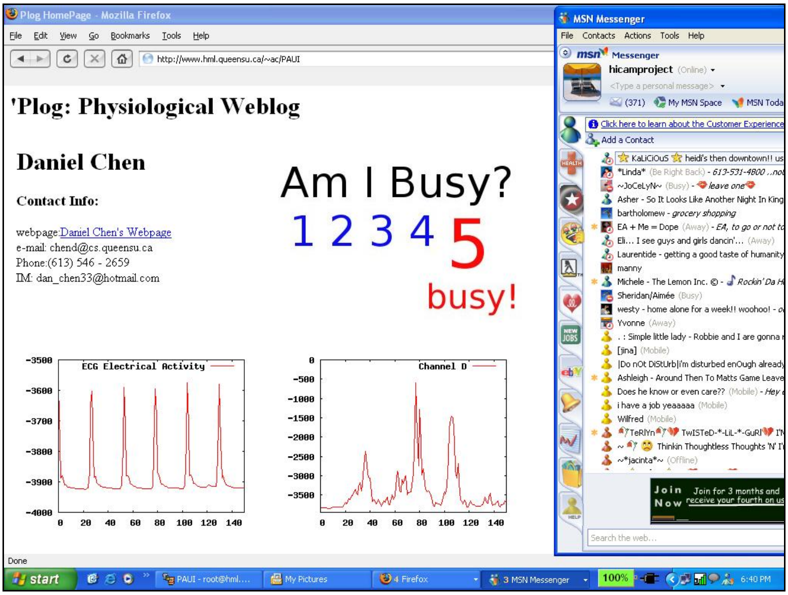

Fig. 8. Screenshot of the physiological weblog displaying the user's predicted level of interruptability

awareness of the interruptability of others, thus facilitating informed decisions on availability prior to actual communication. As such, we expect 'Plog to act as an attentive notice board that could reduce the number of inopportune interruptions by emails, instant messages or telephone calls. As a future direction of this work, we hope to evaluate the effectiveness of the 'Plog system as a means for determining and communicating user availability.

8 Conclusions

In this paper, we presented a preliminary study of the use of physiological measurements for predicting user interruptability status. We measured Heart Rate Variability (HRV) and Electromyography (EMG) signals whilst users performed a variety of tasks, including reading, solving word puzzles, mental arithmetic, typing, and playing a racing game. Results show high correlations for both HRV (r = 0.96) and EMG (r = 0.85) measures with user self reports of their interruptability. We combined these two measures into a single linear model, which predicted user interruptability with a combined r^2 of 0.95, explaining 95% of the variance. We note that our model describes interruptability across users, rather than per individual, and as such should be considered preliminary. We presented an application of our findings in the Physiological Weblog, or 'Plog, a system that uses our model of interruptability for automating online messaging status.

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