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The Physiologically Attentive User Interface

Towards A Physiological Model of Interruptability

by

Daniel Chen

A thesis submitted to the
School of Computing
in conformity with the requirements for
the degree of Master of Science

Queen's University
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Abstract

This thesis addresses the problem of managing interruptions from computing devices and appliances in a Ubiquitous Computing (UbiComp) environment. One way of approaching this problem is through the use of Attentive User Interfaces (AUIs). AUIs sense the users' attention for objects and people in their environment, in order to avoid today's ubiquitous patterns of interruption. However, current AUIs depend on *overt* measurements of user attention, such as eye contact, which may not always accurately indicate a user's availability for notifications or interruptions. Although overt measures of user attention may tell us that a user is performing a given task, they do not necessarily indicate the *covert* state of mind of the user. This thesis presents an experimental study to develop a novel physiological model of *interruptability* for outside communications that is based upon the user's *internal* state which is *independent of the user's current task.* These models of attention are the basis of Physiologically Attentive User Interfaces (PAUIs), novel interfaces that are physiologically aware of the user's state of mind. PAUIs mediate interruptions reaching the user to automate the regulation of mental load. A number of PAUIs were developed, including the Physiological Weblog, or 'Plog, a PAUI web application which uses the novel interruptability model to automate the *communication* of attentive information to others.

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Acknowledgments

I would like to thank my supervisor, Dr. Roel Vertegaal for his guidance and insight. I would like to thank the other members of the HML for their constructive feedback and support over the years. Also, I would like to thank my previous colleagues Saman Sadeghi and Dr. Steve Mann for inspiring my early work in physiological computing and signal processing. I would also like to thank my mother, Chia Chen, for nurturing my early interest in science and her unwavering support in all my endeavours.

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Contents

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Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

List of Tables

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

List of Figures

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Chapter 1

Introduction

1.1 Motivation

Human Computer Interaction (HCI) as a field of computer science has undergone significant changes over the years. Early computers were mainframe machines often large enough to fill rooms, and operated by a team of specialized users who interfaced with these machines using punch cards or ticker tape.

When the Personal Computing (PC) Era emerged, the stand-alone computer became a *tool* accessible to the average user. The many–to–one relationship between people and computers became a one–to–one relationship. Input methods became more personally focused, and as more users began to use computers professionally, more attention was given to Human Computer Interaction (HCI) as a field. During this time, the mouse and keyboard became universally popular, as did the desktop metaphor, also known as the Windows Icon Menu Pointer (WIMP) paradigm.

With shrinking hardware and increasing device connectivity, our society is now entering what has been described as the Ubiquitous Computing (UbiComp) Era [64].

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In the UbiComp Era, devices pervade every aspect of our lives. This has meant that previous interaction paradigms have begun to break down for a number of reasons:

1. Users no longer depend on a single computer as a tool for all their needs, but rather use several devices, each with their own unique purposes and interaction properties.
2. The increasing mobility of these devices, and their smaller form factor has meant that previous desktop metaphors designed during the PC Era may not always be appropriate.
3. Whereas in the PC era, there was mainly a connection between a single computer and single human, the UbiComp Era has introduced *constant* connectivity between various devices and people.

For many users, interacting with multiple devices on a daily basis has become a daunting task. Devices are becoming *active* communicators, despite being ill equipped to negotiate their communications with humans. As an example, most email programs interrupt a user without considering if the user is available or not. Ubiquitously connected devices have presented new disruptions to our lifestyle and work flow, as many–to–many relationships have led to more frequent interruptions at inopportune times. Rather than enabling us to multi-task, these devices bombard us with messages when we least expect them to.

Researchers have explored new ways to help people cope with Ubiquitous Computing environments by making computers more considerate [25], so as to introduce more sociable forms of interaction with devices. Amongst these are Attentive User Interfaces (AUIs) [58], user interfaces which aim to support the users attentional capacities by sensing their attention for objects and people in their every day life. By sensing externally observable user information such as gaze direction, present AUIs

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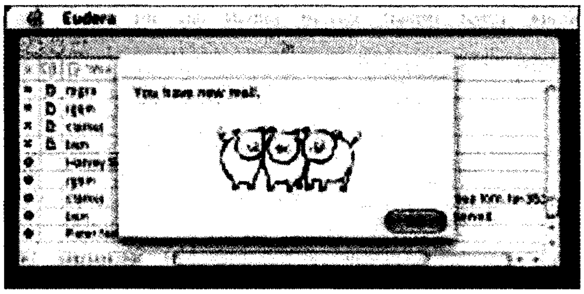

Figure 1.1: Email and other notifications from ubiquitous computing devices create interruptions to users at inopportune times. This figure reproduced with permission from Dr. Roel Vertegaal [57].

can understand the current visual focus of the users and negotiate the communication of devices to support the users task focus [53]. An example is the EyeReason system [53], which assesses a users gaze direction to determine when devices should respond to user commands, and when they should take the dialogue initiative [53]. AUIs may also take the more direct approach of mediating information from the environment to the user, through a process called *mediated reality.* Here, the computer senses the users current attention in order to regulate the amount of information being perceived. An example of such interface is the attentive head phones [57], which regulates office distractions based on the users focus, selectively blocking and conveying external sound depending on context.

1.2 Problem

This thesis addresses the problem of managing the overwhelming interruptions which are generated by Ubiquitous Computing environments. These frequent interruptions

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lower user productivity by disrupting task flow [19]. Current applications, such as instant messaging clients, provide some basic mechanisms for managing interruptions. Users communicate their level of interruptability by manually toggling a status bar seen by others. However, this may become inconvenient when a user is busy and neglects to update their status.

To address this problem, this thesis must examine a more accurate measure of a users interruptability. Having such a valuable measure, enables applications which manage interruptions to automatically determines a user's current availability to communications, and respond appropriately. In prior work, researchers relied mostly upon *overtly* or *externally* observable information such as typing patterns or use of motion sensors. External sensors though [24], such as using accelerometers or gyroscopes, may provide conflicting or inaccurate information.

Even when performed correctly, these current techniques can only assess overt physical activity rather than covert mental activity. For instance, users that are engaged mentally with a task may not exhibit any obvious physical activity. A user reading may be highly focused yet show very little physical movement. Conversely, a user who is biking may not be highly focused but is conveying physical action. Interruptability, then, may not be a function purely of physical exertion, but must also include mental exertion, one that is covert. Current interruptability models lack internal metrics, one that better reflects the users actual mental exertion, and would be independent of external factors or tasks.

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1.3 Approach

In this thesis, user interruptability was modeled upon *internal* metrics, using physiological sensors. Physiological sensors can measure what is happening *inside* the user, and as such may provide more accurate *internal* representations of the users attentive state. In order to explore a novel physiological model of interruptability, a study was designed and conducted with human participants. These lab experiments provide empirical evidence for a novel linear model of interruptability based on Heart Rate Variability (HRV) and electromyogram (EMG) activity measures.

Based upon this physiological model of interruptability, it became possible to use this information to create novel Attentive User Interfaces (AUIs) which could effectively manage incoming interruptions. Such *Physiologically* Attentive User Interfaces (PAUIs) are physiologically responsive interfaces which cater to the user's attentional needs. For example, PAUIs could automatically detect a user's interruptability and communicate or notify their availability to others, so as to reduce unnecessary interruptions.

1.4 Contributions

This thesis's main contribution is the Physiologically Attentive User Interface (PAUI). A number of developments contributed towards the creation of Physiologically Attentive User Interfaces:

1. The first contribution of this thesis is a novel model of interruptability based

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upon physiological measures. This physiological model of interruptability extends the area of interruptability research by providing an *internal* representation of user attention.

2. Based on the previous contribution, the second contribution of this thesis is the creation of a number of PAUI applications. In this thesis, PAUI applications used the physiological model of interruptability to manage or reduce mental load for users. From a broader perspective though, the creation of PAUIs extends the field of Attentive User Interfaces (AUIs), by enabling AUIs to sense the user's mental engagement or *internal* attentive state.

1.5 Overview

We begin this thesis with a discussion of the background covering Attentive User Interfaces (AUIs), Wearable Computing (WearComp), attentive wearable computers and Mediated Reality (MR), and the modeling of interruptability. Next, we examine the development of physiological modeling of interruptability towards the creation of Physiologically Attentive User Interfaces (PAUIs). Following that, we detail how physiological measures were acquired through specific algorithms and numerical techniques developed or adapted during the course of the thesis. Following that, we present physiological modeling of attention using the aforementioned physiological measures, and in particular an empirical evaluation that has led towards a novel physiological model of interruptability. Then, based upon a PAUI architecture, various PAUI applications are discussed which make use of the physiological models of attention and interruptability to manage interruptions or reduce mental load on their

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users. Finally, the thesis ends with a discussion of future work and conclusions.

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Chapter 2

Background

2.1 From Personal to Ubiquitous Computing

In the early days of computing, providing input to computer systems was often difficult. Computers were large machines that could often fill rooms and required teams of users with specialized knowledge to correctly communicate with them using machine language interfaces. Later machines required the use of a command line interface that provided only text-based symbolic input.

It was during the Personal Computer (PC) Era, that the mouse emerged as a primary input device for humans, one that allowed users to more easily communicate with computers, harnessing computing capabilities for everyday tasks. The mouse allowed for pointing and selection of virtual objects in a Graphical User Interface (GUI), enabling the average user to easily use the computer. Many decades since its invention, the mouse remains by far the most efficient interaction method for the desktop computer, with few changes to its design along the way. Douglas Engelbart [21], the mouse's inventor, saw input devices as a way to *augment* human intellect [22] by

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extending our capabilities. The purpose of input devices, according to Engelbart, was to enable human use of computers as *tools* to accomplish specific daily work tasks not only to perform large scale scientific computation as before.

However, the capabilities of PC Era input devices are being challenged in a Ubiquitous Computing environment. Unlike the PC Era, there is now a growing need to interact with many computers or computational devices which seem to pervade our daily life. Ubiquitous Computing (UbiComp), a name first coined by Mark Weiser [63], describes this emerging era where there are *many–to–many* interactions between humans and devices. As these devices become more connected, they behave less like the *tool*–like devices of the PC era, but rather are becoming *active* communicators. Despite being unable to negotiate communication with humans appropriately, these many devices may disrupt users at any given time. Examples include the ubiquitous cell phone, or devices such as the Blackberry [2] which require focus to operate and which may alert us at any time.

To stay true to Engelbarts vision of computers' augmenting human intellect [21], researchers must find a way to harness the computational abilities of devices, rather than let them overwhelm users. Weiser [63] once described this necessary adaptation through new interaction paradigms, "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it." As processors continue to miniaturize, these technologies are becoming embedded in the very fabric of our everyday lives. One of the primary problems users face is how to interact with these multiple devices. In the Ubicomp Era, users are increasingly finding themselves surrounded with devices which each require the user's attentive or mental resources, and constantly interrupt a user during

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their day. In order for humans to co–exist with these devices, it becomes necessary to design what Weiser described as *calm* technology [65], "A calm technology will move *easily* from the periphery of our attention, to the center, and back. "However, designing calm technology that quietly moves between the user's focus and back to the periphery without inducing information overload has been challenging.

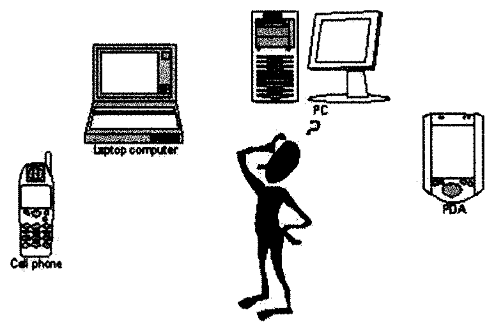

Figure 2.1: Ubiqutious Computing has overloaded users with interruptions from a variety of different devices

2.2 Attentive User Interfaces

To manage interactions with many computers, Vertegaal et al. [58] proposed a framework for *Attentive User Interfaces.* According to Vertegaal et al. [58], Attentive User Interfaces (AUI) optimize device communication with users through the sensing, regulation, augmentation and communication of the user's attention. By being *considerate* of the users current state of attention, AUIs are able to move between the user's focus and back to the periphery.

The Attentive User Interface is a broad paradigm that is applicable to UbiComp

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environments. Five key properties [58], allow Attentive User Interfaces to effectively manage the attentive resources of their users:

1. *Sensing attention*: By tracking users physical proximity, body orientation and eye fixations, interfaces can determine what device, person or task a user is most likely attending to.

2. *Reasoning about attention:* By statistically modeling simple interactive behavior of users, interfaces can estimate user task prioritization.

3. *Communication of attention:* Interfaces should make available information about the users attention to other people and devices. Communication systems should convey whom or what users are paying attention to, and whether a user is available for communication.

4. *Gradual negotiation of turns:* Like turn taking, interfaces should determine the availability of the user for interruption by a) checking the priority of their request; b) progressively signaling this request via a peripheral channel; and c) sensing user acknowledgment of the request before taking the foreground.

5. *Augmentation of focus.* The ultimate goal of all AUIs is to augment the attention of their users. Analogous to the *Cocktail Party Phenomenon* [60, 62], where users are able to focus on a single speaker during a multi-party dialogue, AUIs may, for example, magnify information focused upon by the user, and attenuate peripheral detail.

To better understand the concept behind the AUI, consider the example of modern traffic light systems which augment the attention of all the users involved. Modern traffic light systems use presence sensors in the road surface to *sense* each vehicle's targeted attention. They are programmed with models that determine the priority of traffic on intersection roads with volume statistics, in effect, allowing for *reasoning* about where the user's attention is focused. Using peripheral displays, such as traffic lights, they *communicate* the collective attention of drivers. As such, they *negotiate turn taking* on intersections to allow for smooth traffic flow. Thus, the AUI perspective

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can address many usability issues with devices by preventing potential "collisions" that may arise in a many–to–many information environment.

Sensing the directed attention of humans as opposed to vehicles at an intersection may not be as easy. However, research has shown that human eye contact indicates with about 82% accuracy whether a person is being spoken or listened to in four-person conversations [61]. Essentially, eye fixations reliably indicate the target of a persons attention, including their conversational attention. By implementing user eye gaze as an extra input channel in computing systems, it becomes possible for devices to sociably communicate with their users. Devices which can sense their users attention can determine whether a user is attending to them, or to another device or person. By tracking whether a user ignores or accepts requests for attention, device interruptions can be made more subtly or blocked altogether.

The invention of the Eye Contact Sensor (ECS), brought eye contact to to the forefront of Attentive User Interfaces, just as the mouse brought manual pointing to the GUI. The ECS consists of a set of infrared Light Emitting Diodes (LEDs) mounted around the camera lens. When flashed, these produce a bright pupil reflection ("red eye effect") in human eyes within range. Another set of LEDs is mounted off-axis flashes to produce a similar image composed of black pupils. By syncing the LEDs with the camera clock, a bright and dark pupil effect is produced in alternate fields of each video frame. A simple algorithm can then locate the eyes of the user by subtracting the even and odd fields of each frame [23]. The LEDs also produce a reflection from the eyes' surface, these "glints" appear near the center of the detected pupils when the onlooker is looking at the camera, allowing the sensor to detect eye contact without any calibration. ECSs can then stream information, over the

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wireless internet, about the number and location of pupils, and whether these pupils are looking at the device. When mounted on any ubiquitous device, the ECS can sense eye contact with the device at up to a three meters distance. By mounting multiple ECSs on a single device, and by networking all ECSs in a room, eye fixations can be tracked with great accuracy throughout the users environment.

By deploying ECSes throughout the surrounding device environment, Attentive User Interfaces can regulate notifications or interruptions from ubiquitous devices in a manner analogous to how traffic lights direct traffic. For example, EyePliances [53] are smart ubiquitous appliances equipped with ECSs that can sense the users visual focus. All EyePliances then report to a personalized server, called EyeReason, whether a user is working with them based upon eye contact. EyeReason then determines or *reasons* what that user's focus is by tracking of manual interactions and eye contact with the current device. Also, the EyeReason server has been preset with the user's preferred notification channels and a specific prioritization of incoming notifications. Based upon all this knowledge, the EyeReason server can intelligently regulate notifications from devices to adapt to the attentive needs of the user and minimize unnecessary interruptions.

2.3 Wearable Computing (WearComp)

In EyeReason, a server was locally available to help reason about the user's attention, however often there may not be computing resources available in the environment. In these cases, it becomes practical to have a single wearable computing device to create the necessary AUI to negotiate with interruptions or notifications from the surrounding environment. Also, rather than depend on the existence of attentional

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sensors, such as ECSes, to be already deployed throughout the environment, it may also make sense to wear such attentional sensors on the body. Having such a wearable system allows the user to maintain an AUI, even in unprepared environments or situations. As shrinking hardware becomes increasingly wearable, the field of wearable computing or WearComp [38, 66] will begin to play a significant role in our daily lives and the development of future AUIs.

2.3.1 Mediated Reality

Steve Mann [38], first proposed that the wearable computer (WearComp) with its close proximity to the body, could act as an intermediary to the world by regulating or mediating the personal space around us [38]. Through WearComp, *Mediated Reality* (MR) enables the user to experience a computationally modified version of reality.

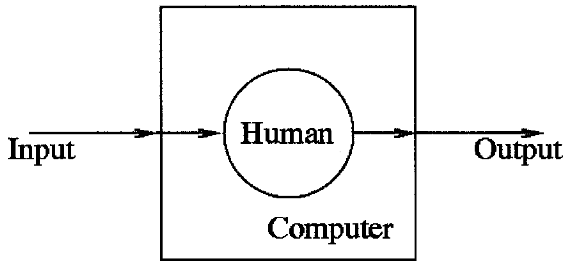

Figure 2.2: Mediated Reality allows the computer to form a "bubble" around the human, such that the incoming information reaching the human's senses can be computationally mediated. The arrows in the figure above show the signal pathways of incoming and outgoing information. This can be a powerful approach towards reduction of mental load. This figure reproduced with permission from Dr. Steve Mann [41].

Most researchers have focused on the *visual* aspects of mediated reality through

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personal imaging devices such as the EyeTap [38, 40] which allow the computational mediation or modification of a users perceived reality. One subset of mediated reality is Augmented Reality (AR), where relevant virtual content is added to the users view of the world to improve the experience. While another subset is Diminished Reality (DR), where the computer functions to *subtract* certain aspects of the real world from the users experience. Essentially, Mediated Reality describes the means by which a wearable computing device can control how information reaches and leaves a user. Mediated Reality enables a computer to form a protective bubble around users, to help manage the information overload associated with a ubiquitous computing environment, as see in Figure 2.2.

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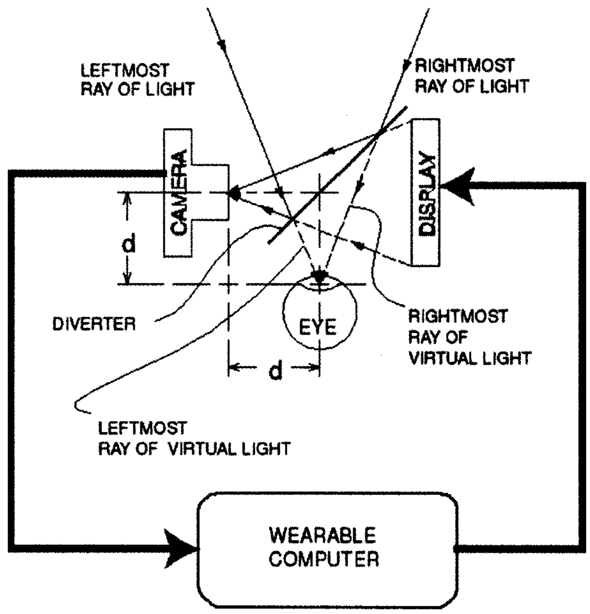

Figure 2.3: Shows the EyeTap arrangement that allows for mediation of a user's perceived visual perceived by merging the real world with the computer world. Incoming light rays are reflected into a sensing element, such as a camera, by a 'diverter, an optical element coated on both sides in reflective or semi-reflective material. These diverted light rays are digitized by the sensing element and then the light data is computationally processed by a wearable computer. The resynthesized light data is then outputted by a micro-display, which projects the resynthesized light back onto the diverter which then reflects the beams into the eye. This figure reproduced with permission from Dr. Steve Mann [41].

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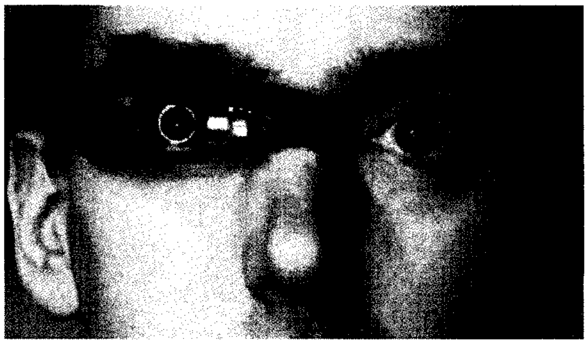

Figure 2.4: New injection molded design. From this figure we see how the camera has been effectively mapped to the position of the human eye by the EyeTap configuration as outlined in Figure 2.3. What looks like a "glass eye" is the image of the camera lens seen in exactly the same location and depth plane as the wearer's right eye. The camera is mounted on the nose-bridge, and the camera lens is facing toward the wearer's right, but the 45 degree diverter reflects rays of eyeward bound light into it, so that we see it as if it were inside the wearer's right eye. This figure reproduced with permission from Dr. Steve Mann [44].

Humanistic Intelligence

To push forward the areas of Wearable Computing (WearComp) and Mediated Reality (MR), a descriptive signal processing framework called Humanistic Intelligence (HI) [39, 37] was first formalized at the M.I.T. Media Lab. Unlike Artificial Intelligence (AI) which aims to replace human intelligence, the aim of Humanistic Intelligence is to extend the capabilities of humans with computers by taking advantage of the unique neural network known as the human intellect. Wearable Computing systems and Mediated Reality, according to the H.I. framework, must obey certain criteria in order for the human to benefit from the human–computer operational synergy.

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Mann outlined criteria for Humanistic Intelligence [41] in the following six properties:

1. *Unmonopolizing of the user's attention:* The computer does not cut you off from the outside world like a virtual reality game or the like. You can attend to other matters while using the apparatus. It is built with the assumption that computing will be a secondary activity, rather than a primary focus of attention. In fact, ideally, it will provide enhanced sensory capabilities. It may, however, mediate (augment, alter, or deliberately diminish) the sensory capabilities.

2. *Unrestrictive to the user:* The computer is ambulatory, mobile, roving; "you can do other things while using it". E.g. you can type while jogging, etc.

3. *Observable by the user:* The WearComp can get your attention continuously if you want it to; within reasonable limits (e.g. that you might not see the screen while you blink or look away momentarily) the output medium is constantly perceptible by the wearer.

4. *Controllable by the user:* The user has direct operation of the wearable computer.

5. *Attentive to the environment:* The computer is environmentally aware, multimodal, multisensory. (This ultimately increases the user's situational awareness).

6. *Communicative to others:* The computer can be used as a communications medium when you want it to.

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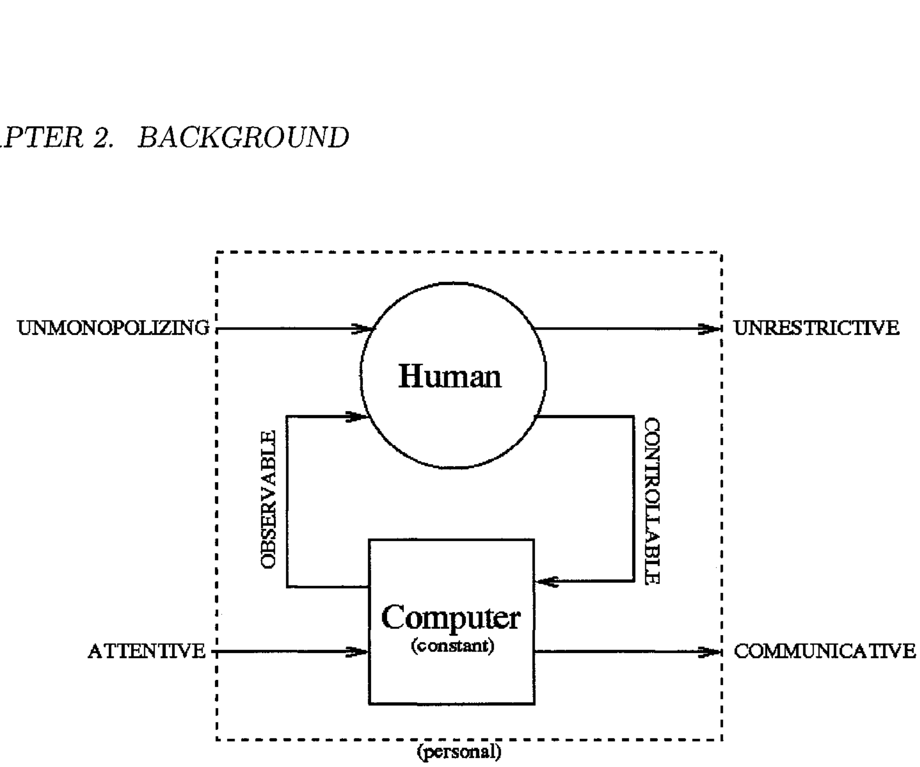

Figure 2.5: The Humanistic Intelligence (H.I.) Framework. The arrows in the diagram illustrate the signal pathways for which information flows between the user, the computer and the surrounding environment. The properties that allow Human and Computer to work in synergy are clearly labelled with each particular signal flow. This figure reproduced with permission from Dr. Steve Mann [41].

The HI framework alludes to the importance of creating attentive computers, particularly in its fifth property, referring to *environmental attentiveness.* When this particular property is combined with Mediated Reality, it enables the creation of interfaces that adapt to the surrounding environment to satisfy the user's attentional needs. In this way, wearable computers, which constantly function in close proximity to our bodies, could then help mediate information reaching the user and help regulate the varying load of attentional resources associated with the user's personal space and daily experience.

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2.4 Attentive Wearable Computers and Mediated Reality for Reducing Mental Load

Mann had previously suggested that by creating an environmentally attentive wearable computer, one could mediate the users reality by filtering extraneous or distracting information before it even reaches the users senses. For example, Mann et al. [41], have described a diminished reality system that blocks advertisements from the human visual system, to reduce unnecessary mental load on the user. The Reality Window Manager (RWM) [27] creates a mediated reality windowing environment using the VideoOrbits algorithm [1, 43], in which window terminals and various content can be affixed to real-world planar regions to block out distracting surrounding visual information (such as advertisements). In this way, advertisements determined to be unnecessary to the user, could be blocked out and replaced instead by something more task relevant, such as a windows terminal.

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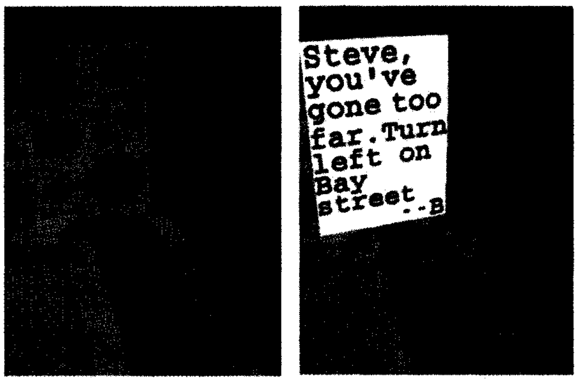

Figure 2.6: EyeTap enables mediated reality. The Reality Window Manager (RWM) makes use of an EyeTap allows and an attentive wearable computer to sense advertisements in the environment (left) and block them accordingly to reduce visual mental load on the user (right) This figure reproduced with permission from Rosco Hill [27].

In many other cases, a Mediated Reality approach can remove disruptive auditory distractions. The Attentive Headphones [57] are such an example of *audio* Mediated Reality, consisting of a pair of noise canceling head phones augmented with a microphone and an Eye Contact Sensor (ECS). Normally, noise canceling head phones block out all noise around the user, however, this isolates the wearer from the attention of his co-workers. With the addition of ECSs, the Attentive Headphones becomes aware of when someone else makes eye contact with the wearer and consequently opens the wearers audio channel by turning off the noise cancellation. The Attentive Headphones block out unnecessary auditory distractions, based on attentive knowledge of others in the surrounding environment. This allows the user to concentrate on their current task. Like the RWM discussed earlier, AUIs such as the Attentive Headphones can enhance cognitive processes through use of Mediated Reality.

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Figure 2.7: The Attentive Headphones allow us to mediate incoming audio using an ECS and noise canceling headphones, such as to augment focus and reduce extraneous interruptions and noise. This figure reproduced with permission from Dr. Roel Vertegaal [57].

2.5 AUIs for Managing Interruptions

As discussed in Chapter 1, this thesis addresses the problem of users overwhelmed by interruptions. These interruptions bombard them from their cell phone, and other mobile devices running their email and instant messaging clients. In an approach similar to Mediated Reality, AUIs help users cope with these interruptions by mediating device notifications before they reach the user's sense. Before notifying the user, AUIs must reason about the importance of their devices message relative to the

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users current activity [29], and consequently decide whether the user is available or not to receive the message.

In order for AUIs to respond dynamically to the users attentional state, AUIs usually measure the users attention for devices and tasks. However, to truly determine whether a user is available or not for notifications, researchers have focused on finding a way to measure how *interruptable* a user is.

2.6 Modeling Interruptability

Researchers have previously modeled *interruptability*, to know how available a user is to notifications and communications [11, 14]. This research has usually rested upon measuring *externally* observable user behaviors to conclude how busy a user was. For example, Horvitz et al. [29, 32] approached the problem using Bayesian reasoning models that allowed prediction of user interruptability on the basis of measuring a variety of interactive behaviors. They created attention-based models based upon analysis of keyboard and mouse events during interactions with applications such as, for example, email clients. Horvitz et al. also measured the effect of interruptions by calculating the Cost of Interruption (COI), from user feedback on video recordings [30]. The COI varied according to the user's attentive state, 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 COI. Horvitz et al. [28] applied their Bayesian reasoning models in the Lumiere project, which was used to provide automated assistance in popular software applications.

Hudson et al. [33] used a "Wizard of Oz"study approach, where they gathered attention-based data by visually reviewing video–recorded user interactions in a mock

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office setting for later statistical analysis. Meanwhile, they used a "beeper" study 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 visually observable physical activities [24].

In [54], Siewiorek et al. presented SenSay, a context-aware mobile phone that senses 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 physical movement, and any audible noise in the environment. However, the device was limited due to its reliance on external measures in the users surroundings, which are not always related to interruptability.

2.6.1 Limitations of Overt (External) Measures

Similar to the previously discussed approaches to modeling interruptability, current AUIs also depend on *overt* or *external* measurements. For example, in the EyeReason system, the overt visual engagement of the user was measured via Eye Contact Sensors [18]. However, overt measures may not always accurately indicate a users availability to notifications or interruptions. Although overt measures may tell us that a user is performing a given task, they do not necessarily indicate to what degree the user is actually mentally engaged. For example, if an ECS were to measure that a user was looking at a computer monitor, a user could be possibly engaged in a perplexing work task or just as likely gazing at the computer's attractive screen saver. While ECSs may tell which device the user looks at, they can not necessarily distinguish whether the user is simply looking at the device, or actually mentally engaged in

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focused activity with it.

Whether current AUIs employ ECSs or use advance Bayesian models of user behavior [31], fundamentally neither approach provides adequate information about the actual engagement of a user since they remain dependent on *overt* or *external* measures. Also, most models based upon observable user behavior can easily become overly complicated, since they are dependent on *task context.* Some tasks have similar observable user behaviors, but different levels of mental engagement. In addition, if there is a new task unaccounted for by the current model, then the model becomes invalid. Thus, to know if the user is truly mentally engaged, it is necessary to tap into *internal* measures that truly reflect reflect the user's *internal* state. In an effort to address this problem, some researchers have begun to explore how direct physiological *internally* based measures may correlate to a user's actual mental engagement [34].

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Chapter 3

Physiological Modeling of Interruptability

As we saw in Chapter 2, most researchers have depended on overt measures to determine the user's interruptability, but this approach is limited because interruptability is inherently an *internal* measure. However, *physiological sensors* are promising since they directly measure signals that can describe the internal changes and events occurring *within the human body.*

In this thesis, the ultimate goal was to study the use of physiological measures for the automated detection of user interruptability. Doing so meant developing a novel physiological model of the users attentive state or interruptability, which gave a direct *internal* representation of the users attentive state.

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3.0.2 Previous Work with Physiological Interfaces

Affective Computing

In the area of HCI, there has been little use of real-time physiological measures towards modeling user interruptability. Some of the earliest research that combined human-computer interaction with physiology was conducted by Picard et al. [47]. They used physiological sensors to analyze 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) [48] that was 81% accurate in the classification of eight emotional states (including anger, joy, and grief). However, classifying emotions is often difficult, since physiological responses to emotion may vary between people.

Physiological Control Mechanisms

In other work, some researchers have used physiological signals as direct control mechanisms for adaptive systems. For example, Prinzel et al. used the brain's motor signals to make better task allocation decisions, in order to improve adaptive automation system design [50]. Meanwhile, in HI-Cam [42], the mu–related de–synchronization measure [51] from the brain's electroencephalogram (EEG), was used to control the brightness of wearable computer displays. Discussed later in this chapter, the mu-related desynchronization measure shows the user's gross motor activity. This particular measure automated the regulation of brightness control on an EyeTap [38] display such that when the user was engaged in a moving task the brightness decreased and conversely increased when the user was at rest. Although EEG provides

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a valuable measure, its uni–modal application suffers from noise. In further work, by using additional physiological signals, such as the heart's electrocardiogram (ECG), skin conductance, blood pressure, muscle tension and respiration, recognition rates could be improved [15]. However, these previous physiological approaches did not directly measure the user's *interruptability*, rather the adaptive system recognized the user performing a particular task and responded accordingly.

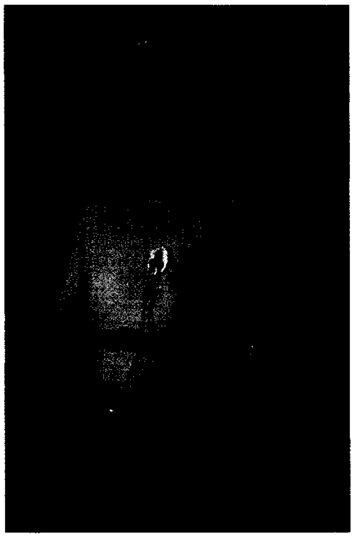

Figure 3.1: HI-Cam Apparatus. The user is wearing a EyeTap attached to a wearable computer, EEG sensors in the baseball cap, and various other sensors along with the ProComp+. This figure reproduced with permission from Dr. Steve Mann [42].

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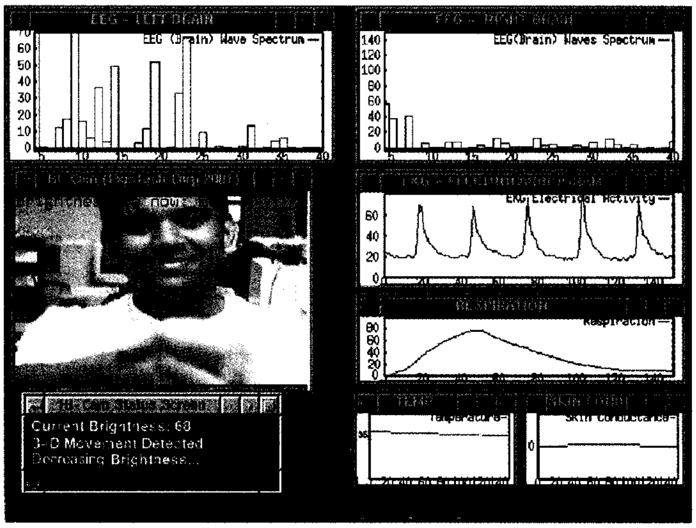

Figure 3.2: A Screenshot of the HI-Cam. The brightness of the EyeTap display is lowered based upon movement detected related to motor activity measures of the EEG signal. This figure reproduced with permission from Dr. Steve Mann [42].

3.0.3 Physiological Measures

Determining Mental Load using ECG

Other researchers, however, have been able to correlate a users innate mental load during a wide variety of tasks with physiological measures. Although mental load may not necessarily be exactly correlated with interruptability, it does provide a starting point for creating such a model. The most common measure of mental load is NASA's Task Load Index (TLX) [26], 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 sub-scales: mental demand, physical demand, temporal demand, performance, effort, and frustration.

Later, Rowe et al. [52] released a preliminary study indicating that mental effort

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may be reflected in the user's Heart Rate Variability (HRV) [45]. The HRV physiological measure which we will discuss in detail in Chapter 4, describes the variability in the rate at which the heart beats. HRV can be found by analyzing the user's *electrocardiogram* or ECG, a graph that shows the electrical activity of the heart. Rowe et al. showed that HRV measures, particularly those that examined the low frequency components of the HRV, correlated well with mental load of users during complex visual tasks [52], as measured by the NASA TLX subjective workload assessment tool [26]. 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 NASA TLX showed significant increases in mental load with task difficulty. According to this work, it was found that the HRV physiological measure correlated well with measures from the TLX questionnaire, with the additional advantage that HRV can be determined in real time.

To understand the physiological reason that the HRV measure acts as an indicator mental load, we must look at the human nervous system itself. 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, the so–called "flight or fight"response. Conversely, the PNS returns the body to normal after sympathetic stimulation by decreasing heart rate and blood pressure to consistent levels. The balance between these two opposing forces is known as the sympathovagal balance, and is thought to affect the cardiac cycles beat-to-beat changes that HRV measures [36]. This balance is affected by

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mental load, since it stimulates the SNS by creating some stress.

Determining Physical Activity using EEG and EMG

To complement measures of mental activity, this thesis also explored potential measures of physical activity, since they may or may not correlate with user interruptability. Previously, physiological measures which correlated to physical activity depended on either the electroencephalogram (EEG) or the electromyogram (EMG), graphs of the electrical activity happening within the brain and muscle respectively.

In the past, EEG was typically used to assess *gross motor movement* through the *mu–related de–synchronization measure* [51]. Typically, the EEG is transformed into the frequency spectrum using the fast fourier transform for analysis. A phenomenon occurs during the onset of motor related activity by the user, there is a sudden power drop in the 8–30 Hz frequency band. Detecting the occurrence of this phenomenon, known as mu–related de–synchronization has been used in previous work [16] on Physiologically Attentive User Interfaces.

However, EEG can be quite invasive because it requires considerable scalp contact and the use of wet electrolytic gels. Another candidate considered was the use of electromyography (EMG) sensors which directly measure 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 by detecting specific muscle contractions throughout the users body.

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Physiologically Modeling User Attention: Heart, Body and Brain

The physiological measures we have discussed for determining mental load and physical activity, can be used to model interruptability through conducting user evaluations. Whereas previous approaches applied these measures separately as control mechanisms, as discussed earlier, this thesis will examine how interruptability can be modeled based upon a number of physiological measures. However, before beginning user evaluations, it is first necessary to develop a number of techniques to acquire these physiological measures from the raw ECG, EMG, and EEG signals emanating from the heart, body and brain respectively. Also, if these physiological measures are to be used later in creating physiologically responsive applications, acquisition techniques must be able to perform in real-time or close to real–time as much as possible.

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Chapter 4

Acquiring Physiological Measures

In the last chapter, we discussed using physiological measures of physical activity and mental load, to model interruptability. To proceed with this goal however, we must first acquire these measures by extracting them from the raw physiological signals.

Physiological signals such as the electroencephalogram (EEG), electrocardiogram (ECG), and electromyogram (EMG), are electrical signals first sensed from the human body by way of a physiological data measurement hardware. This hardware, such as the ProComp+ by Thought Technology Inc. [3], samples the electrical activity at the physiological sensors surface and provides a discrete value. The ProComp+ used throughout this thesis sampled EEG signals at 256 samples per second, and ECG or EMG signals at 32 samples per second. By examining the raw physiological signals themselves it is difficult to extract anything meaningful, so it is necessary to process these discrete signals for precise physiological measures. In this thesis, a number of physiological signal processing algorithms were developed to obtain the necessary physiological measures, such as heart rate variability (HRV) discussed earlier in chapter 3, to develop a physiological model of interruptability.

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4.1 Acquiring Physiological Measures from the ECG

The ECG signal is commonly characterized by the distinctive *PQRST complex pattern* which repeats itself [20]. The alphabetic characters P, Q, R, S and T have been traditionally used by cardiologists to describe the standard ECG signal. The most notable feature of the PQRST complex is its distinctive spike, or R peak, which represents the point in time where the ventricles of the heart became completely depolarized. To determine physiological measures such as the heart rate and consequently the Heart Rate Variability (HRV), the timing interval between each R peak is needed. This graph or array of the time intervals between R peaks on an ECG is known as the *tachogram.*

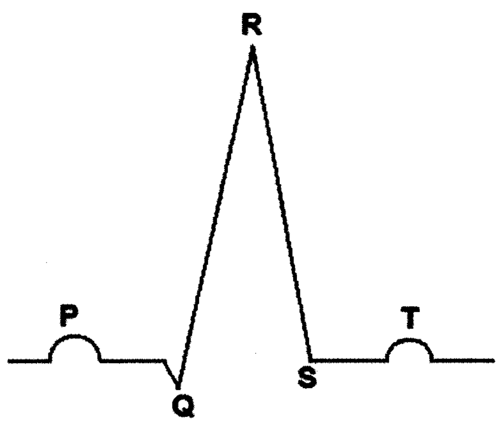

Figure 4.1: PQRST complex pattern of the ECG signal.

In an ideal ECG signal, the flat line or *baseline* that leads to the PQRST complex

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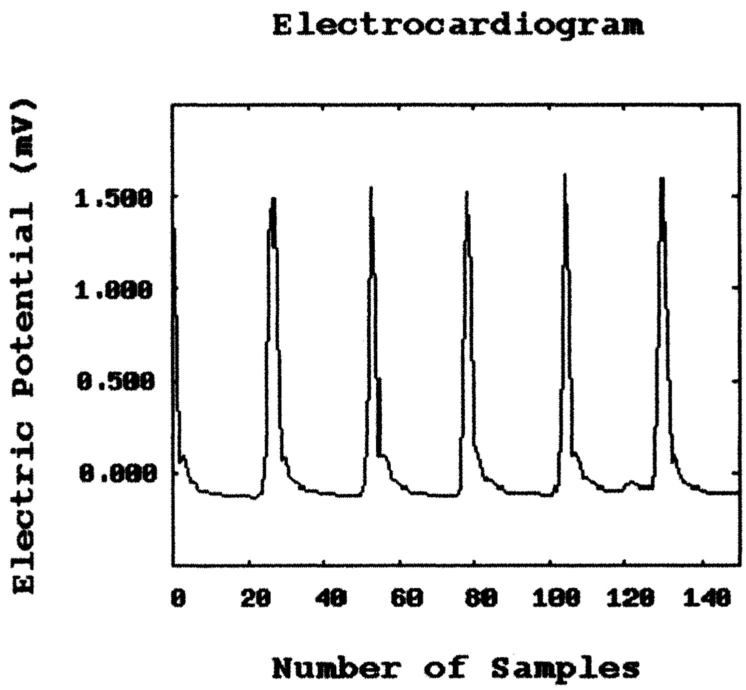

Figure 4.2: Typical Electrocardiogram(ECG) signal. Sampled at 32 samples per second.

remains constant. In practical situations, however, the ECG signal encounters something called *baseline drift*, where the baseline gradually shifts in value up or down due to small changes in the skin conductance from sweat. Also, there may be some noise in the signal from the sensor accidentally moving. In order to detect R-peaks then, one can not apply an arbitrary threshold to the signal. Instead, it is necessary to create a robust peak detection program which is relatively unaffected by baseline drift or noise.

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4.1.1 A Robust ECG Peak-to-Peak Detection Algorithm

The peak detection algorithm developed in this thesis was optimized for recognition of R peaks in the PQRST complex. Although one may use a threshold approach to detect R peaks, as some other researchers do, this threshold must be re–calibrated each time the system is used. This re–calibration is required because of some additional baseline drift that occurs between ECG sessions. To avoid the necessity of calibration, peaks can instead be robustly detected by changes in the *relative values* of the ECG data. The R peak is characterized by a significant rise to a maximum or *peak value*, followed by a sharp constant drop. Thus, the following algorithm detects peaks based upon a large constant drop that follows a local maximum ECG value, which is located at the *peak–location*, with *peak–value*. The algorithm counts the number of peaks for a given array of N discrete ECG data points. For every ECG data point's *current–value* and *current–location*, from 1 to N, the algorithm performs the following actions:

1. **If the ECG data point's *current–value* is more than the last *peak–value*, then the *peak–value* and *peak–location* are updated with the ECG data point's *current–value* and *current–location*.**

   As the *current–value*, and *current–location*, reach closer to the ECG's R–peak, the *peak–value* and *peak–location* are correspondingly updated. However, as the ECG data point's *current–value*, and *current–location* passes the R peak, the *peak–value* and *peak–location* are no longer updated since the current–value is below the peak–value.

2. **If the difference between *the current–value* and the *peak–value* exceeds a certain threshold, this signifies the beginning of a drop from the *peak–value*.**

   This detected drop has been determined to be the result of a local maxima, and so the R peak must be located at the *peak–location*. The current R peak's location is recorded in an array for future calculations.

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3. **Reset the peak–value and peak–location to the current value and current location. Repeat step 1 again.**

At the end of this peak detection algorithm, an array has been produced that contains the locations of each R peak in the ECG signal. From this array, and with knowledge of the sampling frequency, we can produce a *tachogram* by calculating the time intervals (in seconds) between peaks.

4.1.2 Physiological Measures from the ECG

The tachogram, the graph or array of time intervals between R peaks, forms the basis for a number of physiological measures that can be used to interpret the ECG. This section describes a set of physiological measures, or feature variables, that will be later used to explore how ECG signals may correlate with interruptability (see [46] for a more detailed discussion). In the following notation, a tachogram array, x, of size N is used. Each element of the tachogram array, x_k (where $k = 1..N$) represents a successive time interval (in seconds) between consecutive R peaks:

- **ECG Heart Rate (HR)**: The average heart rate (HR) is found by first taking the average tachogram value, to find the average time interval or time period (in seconds), $\overline{x}$, between R peaks (i.e. heart beats).

  $$\overline{x} = \frac{1}{N}\sum_{k=1}^{N} x_k$$

  To convert this into a heart rate, the inverse of the average period is taken to obtain the average frequency of heart beats, in beats per second.

  $$HR_{bps} = \frac{1}{\overline{x}}$$

  However, the conventional measurement units for heart rate are beats per minute (or bpm) so a units conversion must take place.

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$$HR_{bpm} = 60 \cdot HR_{bps}$$

The heart rate can be used to distinguish between higher and lower states of physical activity.

- **ECG RMSSD (Root Mean Square of Successive Differences)**: This measure is calculated by finding the square root of the mean squared differences between successive tachogram elements.

$$RMSSD = \sqrt{\frac{1}{N}\sum_{k=2}^{N}(x_k - x_{k-1})^2}$$

Changes in the successive time intervals between ECG R peaks may describe to some degree the level of variability in the heart rate, and could possibly be correlated to stress levels related to mental load [46].

- **ECG Heart Rate Variability (Time Series)**: Originally, heart rate variability (HRV) was just defined temporally by taking the standard deviation of the tachogram array elements. The temporal definition of HRV [46] is simply defined as the standard deviation s_N by the following equation:

$$s_N = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(x_k - \overline{x})^2}$$

As mentioned earlier, studies have shown that increased HRV could be correlated with increased mental load [52].

- **ECG Heart Rate Variability (Frequency Domain)**: Later, as ECG analysis methods became more sophisticated, a frequency domain definition of HRV became popular amongst physiologists [46]. According to this work, using this frequency based definition of HRV, there is a significant correlation of HRV in the low frequency range (0.04–0.15 Hz) to mental load. In our implementation, the following algorithm was adapted, based on standard guidelines [46], to determine the *Power Spectral Density (PSD)* function of the HRV signal:

  1. The tachogram signal, x_k, is determined using the previously developed peak–to–peak detection algorithm. In our case, we used a 16 data point window of the tachogram, representing approximately the last 10-16 seconds of user's data.
  2. The 16 tachogram points of x_k were then linearly interpolated to, x_y, consisting of 256 points.

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3. This window of interpolated tachogram data, x_y, was transformed according to the Discrete Fourier Transform (DFT).
   For $j = 0...n-1$:
   $$f_j = \sum_{y=0}^{n-1} x_y e^{-\frac{2\pi i}{n} jy}$$
4. The sum of the real powers, $Re|f_j|$ of the resulting discrete signal over the 0.04 - 0.15 Hz range was then used as the HRV metric.

This particular physiological measure may prove useful when studying interruptability, since the resulting power in the low frequency range of the HRV has been shown to vary with user mental load during task performance [52].

4.2 Acquiring Physiological Measures from the EEG

As we saw in Chapter 3, prior studies have shown that the use of a single electrode is sufficient to gather motor–related information from the EEG signal [42]. The following method was used to physiologically measure the EEG event-related desynchronization in the mu–power range (8–30 Hz)as discussed earlier [51]:

1. A discrete fourier transform is applied to an array of size n discrete raw EEG data values, where s_k represents the discrete value of the array's k–th element:

   $$\text{For } k, j = 0...n-1:$$
   $$f_j = \sum_{k=0}^{n-1} s_k e^{-\frac{2\pi i}{n} jk}$$

2. A cut–off frequency filter is applied to the mu-power range of 8-30 Hz.
3. Because the signal varies quickly in time, a 3-tap averaging filter is applied onto the resulting signal to smoothen it for motor-related event detection. The sum of the real power, $Re|f_j|$, of the frequency filtered discrete signal is taken.

During the onset of user motor activity, a decrease in the Mu–power range (8–30 Hz) can be observed in the EEG signal [51].

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4.3 Acquiring Physiological Measures from the EMG Signal

Although the EEG signal is excellent for measuring gross motor movement, it can be difficult to manage because it requires wet electrolytic gels which may be uncomfortable for the user. Dry adhesive EMG sensors, however, are not only easier to apply but they can be applied throughout the users body to measure the activity of specific muscle groups.

In comparison to the ECG, however, the raw EMG signal is quite irregular. The signal is a flat line prior to muscle activity, but it becomes very erratic during contraction. As Figure 4.3 shows, extracting meaningful measures from this signal is therefore more challenging compared to ECG.

The following EMG measures were used in this thesis to quantify the amount of physical activity taking place at any moment:

- **EMG Count Small (EMGCS) and EMG Count Large (EMGCL)**: 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 contractions.
- **EMG Standard Deviation (EMGSD)**: Given a window of EMG data, this feature 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 increase as well.
- **EMG Power (EMGP)**: Given a window of EMG data, this measures the overall power of the EMG signal.

An advantage of the latter two EMG feature variables is that they do not require calibration, since they are based on the relative values within the signal. From these

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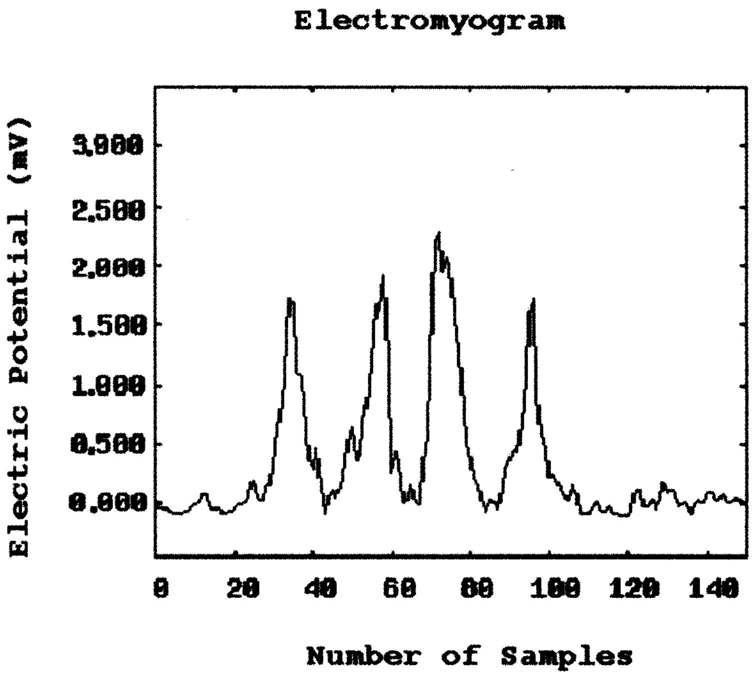

Figure 4.3: Electromyogram (EMG) showing signal increase during muscle contraction. Sampled at 32 samples per second.

signals it is possible to determine the amount of physical activity in specific muscle groups.

In this chapter, we discussed a number of algorithms and techniques to acquire meaningful physiological measures from the ECG, EEG and EMG signals from the human body. Establishing these meaningful physiological measures, which typically indicate mental load or physical activity, provides a foundation to begin physiological modeling of interruptability through conducting user studies.

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Chapter 5

Experiment: Physiological Modeling of Attention

Based on the physiological measure acquisition techniques developed in Chapter 4, it becomes possible to begin constructing physiological models that represent the users interruptability or attention. Our final purpose in this thesis, as we discussed in Chapter 1, is to create useful models for systems to reason about the user's attention. By automatically detecting the users attentive state or interruptability, a Physiologically Attentive User Interface (PAUI) may intelligently mediate the information reaching the user from surrounding devices so as to avoid overwhelming the user with distractions. The experimental challenge though is to create an effective physiological model of attention which can accurately predict when a user is available for notifications or not. In the course of this thesis, two modeling approaches were taken. Firstly, a *PAUI Classifier* which was an initial attempt to determine the user's attentive state based on the most likely activity or task the user was performing. Secondly, an empirical model of interruptability was examined. This second approach was novel not only

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because it physiologically modeled interruptability, but did so *independent* of the task being performed.

5.1 PAUI Classifier: Classifying States And Degrees Of Attention

In the first approach to physiologically modeling user's attention, a classifier was built. This classifier reasoned about the user's attentive state based on the most likely activities or tasks the user was performing. The PAUI Classifier distinguished between various degrees of attentional states by combining multiple physiological signals. As seen in Chapter 3, the ECG's HRV measure, provide indicators for mental activity, but did not necessarily indicate physical action. Meanwhile, the EEG's mu–desynchronization provides a physical activity measure, but is not indicative of mental exertion. By combining the HRV measure for mental load with the mu–desynchronization measure for motor activity, the classifier can predict whether the user is actively partaking in a task, or more passively engaged, all according to readings from the ECG and EEG. It may then be possible to further disambiguate the users activity using information from sensors in the user environment [31] or based on modeling of the user's task habits.

Table 5.1 illustrates the ECG and EEG based classifiers used for modeling the users attentional state. High and low mental load are distinguished based upon the user's ECG signal by detecting changes in the Heart Rate Variability. Meanwhile, gross motor activity is distinguished based upon the EEG signal, by detecting increases and decreases in the mu–power range. Four user states are distinguished that

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	Low Physical Activity (EEG: High mu–power)	**High Physical Activity (EEG: Low mu–power)**
Low Mental Load **(ECG: Low HRV)**	User State 1 Candidate Activities: Pausing, Relaxation	User State 2 Candidate Activities: Moving
High Mental Load **(ECG: High HRV)**	User State 3 Candidate Activities: Driving, Reading Thinking	User State 4 Candidate Activities: Meeting, Lecturing Writing

Table 5.1: Classifying activities according to attentional state.

aid in predicting the availability of users for interruption. Under this scheme, the lowest degree of attention is exhibited in User 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. Meanwhile, User State 2 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. User State 3 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

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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.

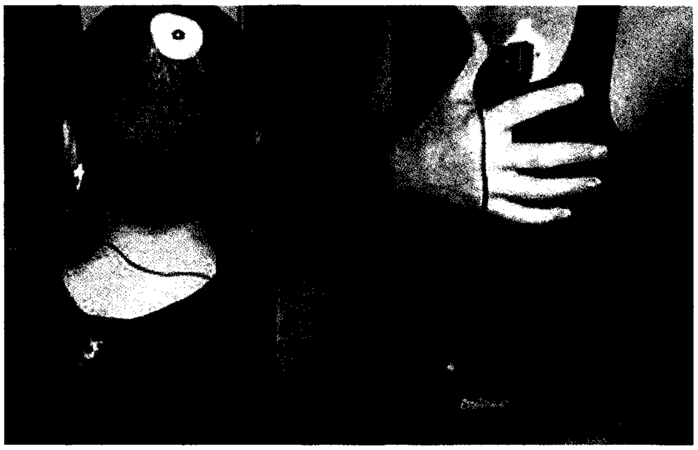

Figure 5.1: EEG sensors (left) provide information on the user's motor activity, while ECG sensors (center) provide information on the users mental load.

Initial evaluations of the classifier showed that it could reasonably identify whether users were available for interruptions or not. A physiologically attentive user interfaces could then be constructed to take advantage of the classifier, such as the PAUI cell phone which will be discussed in Chapter 6 [16].

Although this classifier approach was the first to use internal physiological metrics to reason about availability, it was lacking in a number of ways. The classifier relies upon physiological measures to estimate the probable task the user is engaged in, and consequently is a *task–dependent model.* Sometimes the user could be engaged in tasks that are outside of the model, and so the classifier would have difficulty

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with task identification. Moreover, similar to the deficiencies of Bayesian reasoning approaches discussed in Chapter 3, this model does not account for the fact that a user's engagement with a particular task may not necessarily correlate to how interruptable the user is.

5.2 An Empirical Model of Interruptability

Recognizing the drawbacks of the classifier approach, while drawing inspiration from previous work [16], the goal was to build towards a more generic physiological model of interruptability. In this approach to physiologically modeling interruptability, the aim is to measure physical activity and mental exertion of the user without having to identify specific user tasks. In taking this approach, it becomes possible to *directly* correlate the users *internal* physiological responses to their self–assessed interruptability. In so doing, a task-independent model of interruptability is created based purely on the users physiological state.

From the previous experience with the classifier, it was also found that users were uncomfortable with the use of electrolytic gels for EEG detection of physical activity. So for our next physiological model of interruptability, physical activity was measured with the EMG instead, while mental activity by the ECG.

5.2.1 Evaluation (Experiment 1)

To obtain a generalized physiological model of interruptability, an experiment was designed that related participants self-perceived interruptability to their physiological state as quantified by Heart Rate Variability (HRV) and muscle activity through the

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EMG Standard Deviation (EMGSD) measure. The first experiment used a beeper-study approach similar to that used by Hudson [33], asking participants to verbally state their interruptability whilst performing five different tasks with varying levels of difficulty and physical activity. The second experiment was designed to evaluate the impact of physical exercise on the current model, and compared a sedentary task with an active task on an exercise bicycle.

5.2.2 Participants and Design

A total of nine people participated in the experiment. Participants consisted of six males and three females with a mean age of 24.3 years; all were regular computer users. All nine participants performed all five tasks, with the order of presentation randomized between subjects to counter any ordering effects as much as possible.

5.2.3 Apparatus

A wearable Procomp+ system by Thought Technology [3] was used to continuously sample discrete real-time physiological data from sensors placed on the participants body. Each sensor consists of three silver chloride electrodes with a spacing of 2 cm. The ProComp+ system, as discussed briefly in Chapter 4, samples both ECG and EMG at 32 samples per second, This sampling rate is sufficient for both HRV and muscle activity analysis. The software logged the physiological data with a time stamp for offline analysis. The computer system used a 2.0 GHz Pentium 4 processor, running the Debian distribution of the Linux operating system.

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5.2.4 Sensor Placement

Four adhesive sensors were placed on each participant (see Figure 5.2). 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 trapezius in the right shoulder, the extensor carpi radialis in the right forearm, and the tibialis anterior in the lower right leg.

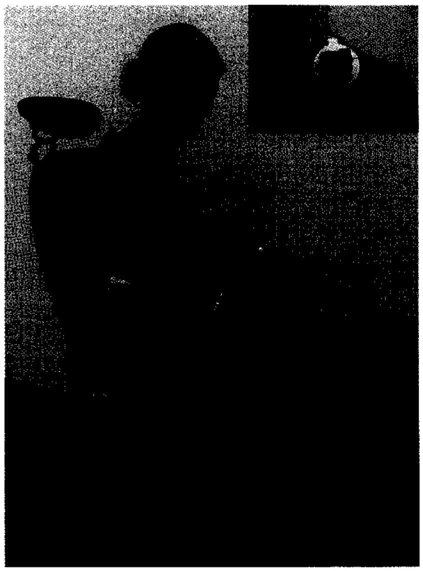

Figure 5.2: Sensor placement, with inset of shoulder sensor.

5.2.5 Task Description

Participants were first briefed about the experiment, during which time they were made familiar with each of the five tasks. The experimenter instructed participants

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that they would be interrupted every 30 seconds to state their interruptability. Participants were told to answer on a scale of one to five, with one meaning that they were completely available for interruptions, and five meaning that they were very engaged and did not wish to be interrupted. Participants remained seated during all tasks.

5.2.6 Task Conditions

The following five tasks were selected for the participants, which ranged in difficulty as well as physical activity:

- *Reading* In this task, participants were presented with a short reading comprehension passage of approximately 1100 words (taken from [4]). In order to encourage more thorough reading, participants were forewarned that they would be tested regarding the passages 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* In this task, 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* In this task, participants were presented with a web-based typing speed test [9]. For fair comparison, all participants were required to type the same passage (an excerpt from "The Adventures of Huckleberry Finn" [56]) for 4 minutes. Participants were allowed to practice for 1 minute prior to the task.

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- *Word Puzzle* For this task, we chose an online anagram puzzle called Text Twist [10]. In this game, 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 2 minutes to find as many permutations as possible.

- *Racing Game* This task required participants to play a racing game on an "XBOX console" [55] connected to a 42 inch widescreen plasma display (see Figure 5.3). We chose the game "Need For Speed Underground 2" [13], as it provides a high-resolution simulation of a driving task. To provide participants with a more realistic experience we used a Madcatz MC2 [7] steering wheel. 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.

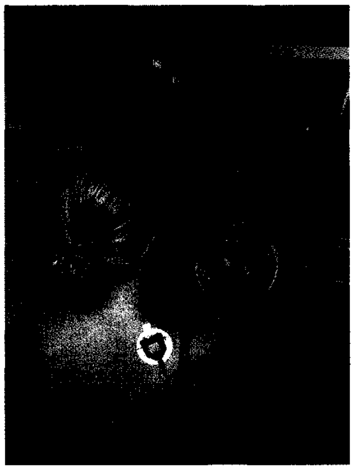

Figure 5.3: Participant performing the racing game task.

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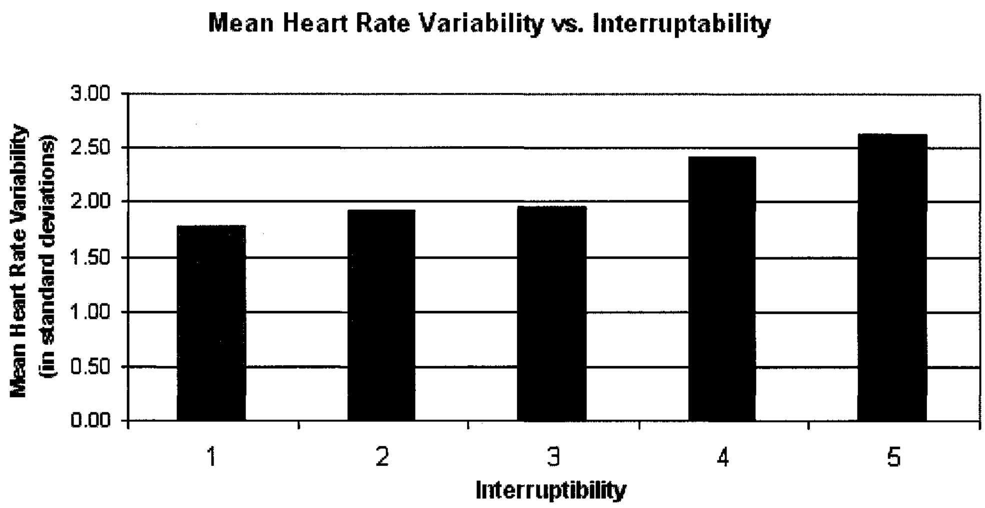

Figure 5.4: Mean HRV levels versus self-perceived interruptability.

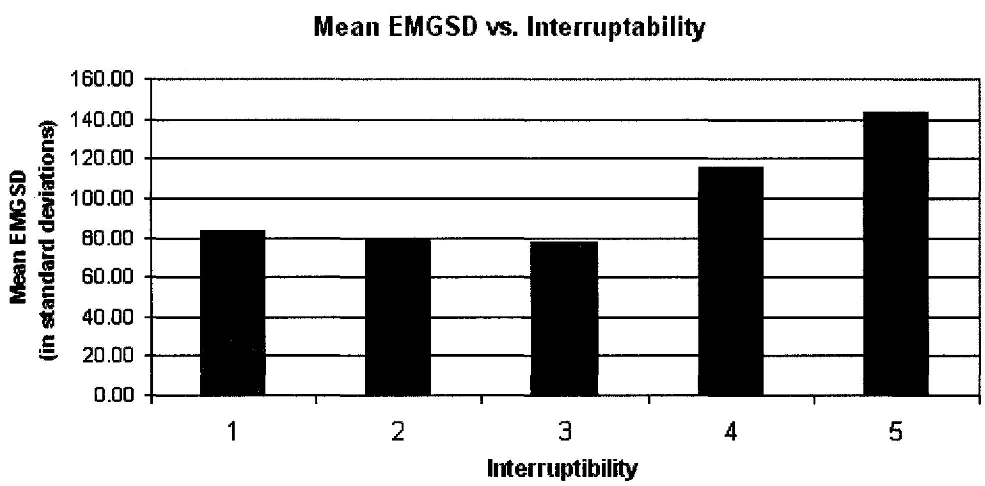

Figure 5.5: Mean EMGSD (muscle activity) levels versus self-perceived interruptability.

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Participant Number	Gender (M/F)	Age	HRV Coeff. (a)	EMGSD Coeff. (b)	Constant (C)	r–value	r^2 –value
1	F	25	0.123	0.020	2.742	0.423	0.179
2	M	25	0.011	0.022	4.25	0.257	0.066
3	M	27	0.104	0.022	2.127	0.515	0.717
4	M	24	0.416	0.000	1.490	0.442	0.196
5	M	25	-0.030	0.001	3.003	0.158	0.025
6	F	22	0.261	0.014	1.378	0.566	0.320
7	M	24	0.049	0.001	3.253	0.355	0.126
8	F	23	-0.033	0.008	3.018	0.726	0.526
9	M	24	0.062	0.005	4.125	0.291	0.084

Table 5.2: Experimental linear regression results for each participant.

5.2.7 Results (Experiment 1)

It was hypothesized that both measures from the ECG and EMG would correlate with participants self-perceived level of interruptability. Physiological measures described in Chapter 4 were used to asses mental load and physical activity. The HRV Time Series metric was used to assess mental load and the EMG Standard Deviation (EMGSD) muscle activity measure was used to quantify physical activity, as these provided the most consistent results.

Figures 5.4 and 5.5 shows the relationship between the self-assessed interruptability and the mean measures for HRV (in standard deviations) and EMGSD (in standard deviations) respectively, averaged over all five tasks.

For further analysis, a linear regression was performed on each participant's experimental data with interruptability as the dependent variable and HRV and EMGSD as the independent variables. Doing this, creates the following linear model:

$$Interruptability = a + b(HRV) + c(EMGSD)$$

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The results of the linear regression are shown in Table 5.2. Taking the mean correlations across all participants, the mean correlation of participants data to this linear model was found to be r= 0.39 and r2=0.226. considering the number of participants in the study these size of the sample pool, these results are good. HRV accounted for the greatest weighting in the model, varying between an absolute coefficient value 0.011 to as high as 0.416, whereas the EMGSD measure varied in its coefficient weighting from 0 to 0.022. In fact, overall the mean absolute coefficient value for HRV was 0.121, much greater than the absolute coefficient value of 0.010 for EMGSD.

5.2.8 Experiment 2

In the first experiment, the only conditions used were sedentary and seated, rather than active and mobile. However, physical exercise may lower HRV due to effects of parasympathetic nervous system dominance [12, 49]. Therefore, to evaluate the use of the model in a mobile scenario, a second experiment was designed that examined the impact of continuous physical exertion, such as biking or walking, on the measures. In the second experiment, the task was to pedal on an exercise bike while simultaneously performing the mental arithmetic task used in the first experiment. In addition to logging HRV and EMG data, the ProComp+ system was also used to record participants current heart rate measured in beats per minute. All other factors remained constant, with the participant verbally notifying the experimenter of their interruptability level during the task.

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5.2.9 Participants and Design

The same nine students participated in this portion of the evaluation, with each participant performing both tasks, in randomized order as much as possible.

5.2.10 Conditions

We used the following conditions to examine the effect of physical exercise:

- *Mental Arithmetic* In this condition, participants remained seated whilst the experimenter read 30 simple mental arithmetic questions, as per the first experiment. Participants were required to answer verbally, and encouraged to answer quickly.

- *Exercise + Mental Arithmetic* Here, participants exercised on a stationary bicycle while responding verbally to a set of 30 mental arithmetic problems. Participants were to maintain a minimum speed of 15 km/h during exercise.

Since the same mental arithmetic questions were presented in both conditions, but in different order, the difference between these tasks was in the amount of physical activity.

5.2.11 Results (Experiment 2)

It was hypothesized that HRV measures would be lower during exercise. It was also predicted that heart rate and EMG would increase with exercise, potentially allowing simple differentiation between passive and active conditions.

Figure 5.6 shows the results of the experiment for heart rate. Not surprisingly, a significant difference was found in heart rate in the biking condition, as compared

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to the control condition ($t(8) = -5.45$, $p < 0.01$). Heart rate during exercise was, on average 37 % higher than in the control condition.

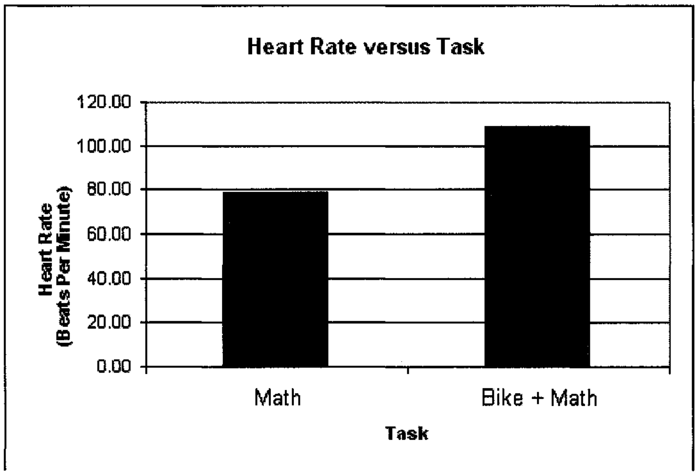

Figure 5.6: The effect of physical activity on heart rate.

It was also found that physical exertion had a direct impact on Heart Rate Variability, with exercise causing a decrease in HRV (see Figure 5.7). HRV was about 65% higher in the control task, as compared to the exercise condition ($t(8) = 4.44$, $p < 0.01$). Obviously, physical exertion also affected muscle potentials (see Figure 5.8), with exercise causing an increase in EMG ($t(8) = -2.74$, $p < 0.05$).

5.2.12 Discussion

Results show that, on average, both HRV and EMG increase significantly with participants self-perceived interruptability level. The model for each participant predicts, on average, up to 22.6% of the variance in interruptability scores, across a variety of tasks. This number is fairly promising considering the number of participants in this study.

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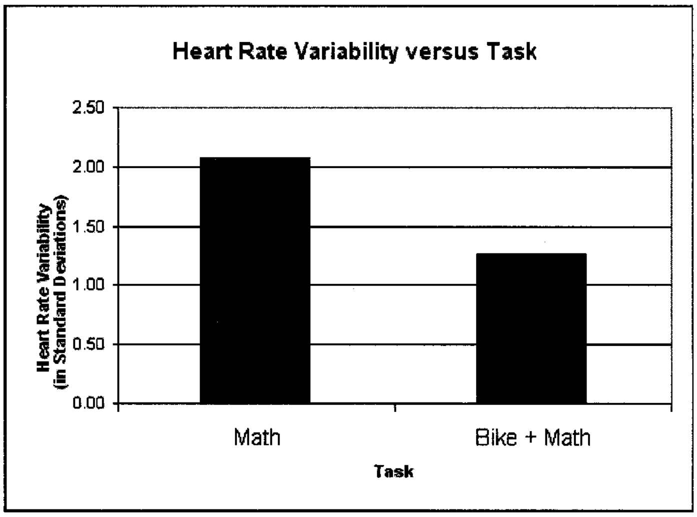

Figure 5.7: The effect of physical exertion on HRV.

From the results of the first experiment, Heart Rate Variability appeared to contribute more to the model than measures of muscle activity. On average the HRV coefficient values were 12 times greater than the corresponding EMGSD coefficient values. While the model is improved by the inclusion of EMG data, it seems that HRV measures of mental load provide a particularly reliable estimate of interruptability. One of the advantages of our empirical approach is that it requires no classification of interactive behaviors, and no individualized statistical modeling techniques. The results are largely in line with prior experiments [33].

However, it must be noted that the measures are affected by the level of physical activity of the user. Results from the second experiment show that HRV measures decrease on average by 65%, while EMG increases on average by a factor 4.4. Effects of strenuous exercise on heart rate variability are in line with prior work [12], and

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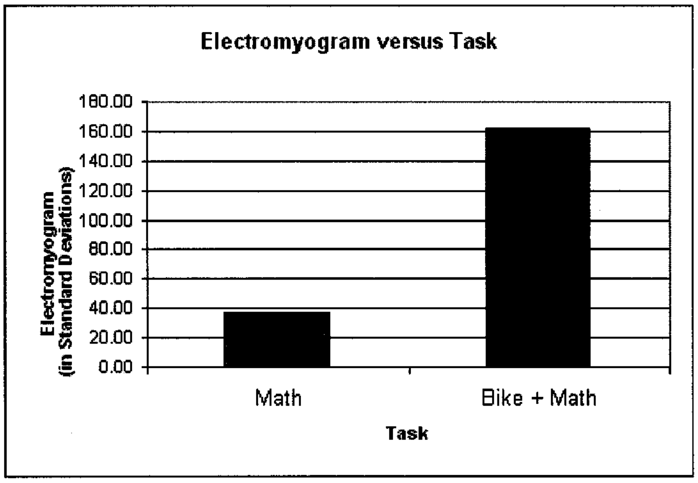

Figure 5.8: The effect of physical exertion on EMG.

most likely explained by the parasympathetic nervous system dominating the sympathetic nervous system during elevated physical activity. The finding shows that when exercising, it is difficult to distinguish between various mental tasks, thus causing the model to break down. As such, the interruptability model can only be applied in scenarios with low levels of physical activity. However, heart rate during exercise was, on average, 37% higher than in the control condition. It seems this feature might be used to distinguish between exercise and non-exercise conditions. It should be noted that the findings are limited in terms of their ecological validity, in the sense that all tasks were completed in a controlled environment. In the future, it would be better to evaluate the use of the model in more realistic task settings.

In this chapter, we began by taking the PAUI classifier approach. However, we found that this physiological modeling approach was often lacking since it still depended on detecting the user performing specific tasks. Following that, an empirical study approach to physiologically modeling interruptability was taken. Heart

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Rate Variability (HRV) and Electromyogram (EMG) measures were quantified whilst users performed a variety of tasks, including reading, solving word puzzles, mental arithmetic, typing, and playing a racing game. Results show fairly good individual correlations with a linear model of interruptability with HRV and EMGSD as the independent variables. This novel linear model predicts user interruptability with a combined r2 of .226, explaining 22.6% of the variance. Based on the modest number of participants in this empirical study, the results proved promising. To test the robustness of these models of attention developed in this chapter, they were applied in the development of Physiologically Attentive User Interface applications.

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Chapter 6

Applications: Physiologically Attentive User Interfaces

Physiologically Attentive User Interfaces (PAUIs) are novel applications that apply physiological models of attention, such as those developed in Chapter 5, to help users better manage interruptions. By automatically determining a users exact interruptability level, a PAUI may take a mediated reality approach, and regulate the information reaching the users senses so as to optimize the users attentive resources, as seen in Figure 6.1. This thesis presents two PAUI applications: i) The PAUI Cell Phone ii) The Physiological Weblog or 'Plog. In this chapter we will see two approaches in which Physiological Attentive User Interfaces (PAUIs) reduce the unnecessary interruptions from overwhelming users. In the first approach, PAUIs may regulate interruptions by directly allowing or blocking information, as in the PAUI Cell Phone. In the second approach, PAUIs may reduce incoming interruptions by informing others of the current user's availability, as in the 'Plog system.

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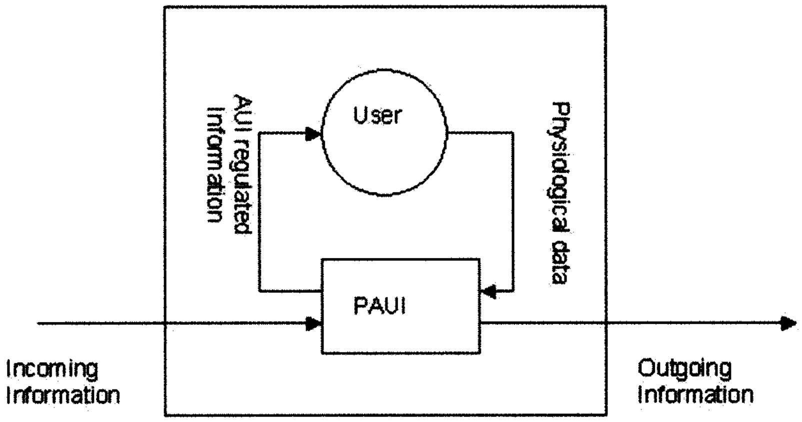

Figure 6.1: Physiologically Attentive User Interface. By using physiological data it becomes possible to create attentive models which can be used to regulate the information reaching the user, reducing mental load when necessary.

6.1 PAUI Architecture

The PAUI architecture was built to be very flexible to accommodate easy development of physiologically attentive applications. Essentially, the PAUI interface layer is a set of physiologically attentive routines that sits above the underlying operating system, providing access to any of the underlying applications and resources through use of unix system calls.

Through this simple architecture, it becomes possible to make *any* unix program or resource physiologically attentive. Just as a GUI event signal can trigger applications, the PAUI layer, traps physiological signals, and calls the appropriate resources to respond accordingly.

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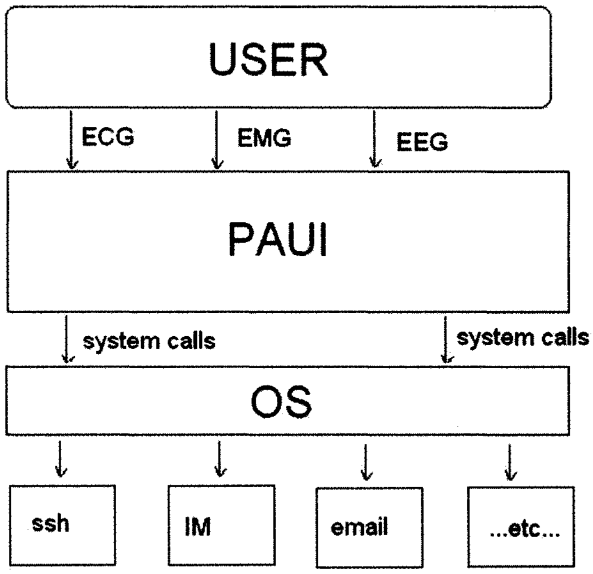

Figure 6.2: PAUI Architecture. Physiological signals such as Electrocardiogram (ECG), Electromyogram (EMG), and Electroencephalogram (EEG) trigger the Physiologically Attentive User Interface (PAUI) to make the appropriate system calls to regulate mental load for the user.

6.2 PAUI Cell Phone

In the first PAUI application, a standard Nokia cell phone was augmented with capabilities for detecting user state as per the PAUI classifier approach (discussed in Chapter 5) to modeling attention. The prototype was based upon the existing AUI Attentive Cellphone design [59]. 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

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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, the PAUI phone regulates the notification level automatically depending on user preferences set for each of the states of attention discussed in Table 5.1 of Chapter 5 (see Figure 6.3). The phone has three optional notification levels for each communication medium: ring, vibrate, or silent mode.

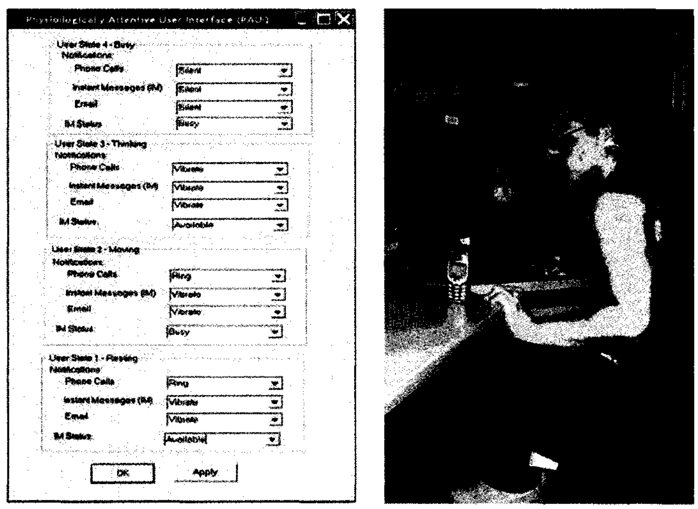

Figure 6.3: The PAUI preference panel (left) allows users to set notifications per user state and per communication medium. User responding to a PAUI phone interruption (right). Preferences may be different for each communication medium, allowing users to differentiate the cost of interruption for email, 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.

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- *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.

6.2.1 Hardware Setup

The PAUI set up consists of three sets of components. Firstly, a wearable Procomp+ system by Thought Technology [3] is used to acquire continuous real-time physiological data. The ProComp+ samples EEG at 256 samples/sec, and ECG at 32 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 phones vibration unit. User preferences for notifications are set directly on the wearable system through a standard GUI (see Figure 6.3).

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6.2.2 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 Figure 6.3). 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 Cell Phone system automatically silences the notification, causing the interruption to be withdrawn.

6.3 The Physiological Weblog or 'Plog

During the development of the PAUI Cell Phone it was realized that perceived interruptions can be reduced not only by direct mediation of a users interruptions, but also simply by *communicating* the users interruptability to others. Communicating

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this valuable information to others allows them to consider the user's availability and reduce interruptions accordingly. An example of this approach would be the toggling of availability status on most instant messenger clients, which lets others know if the current user is busy, away, or available (online).

Another realization during the PAUI Cell Phone's development was that distributing attentive information to others through a cell phone, may not necessarily be the best medium to reach the many possible kinds of mobile devices in a ubiquitous environment. Thus, the experimental findings on interruptability finally were applied in the creation of the Physiological Weblog, or 'Plog, an online updated webpage system that uses the novel physiological model of interruptability for *automating* the broadcast of online messaging status.

6.3.1 Previous Work in Blogging

The use of weblogs, or blogs, has become increasingly popular, with services such as Blogger [5] offering users a convenient online forum to broadcast their daily experiences. With the emergence of camera phones and other mobile imaging devices, many users are capturing their daily lives in order to post them online for others to see. One example of this recent trend is the mobile weblog, or 'moblog [6], a wearable form of blogging. Another example is the movement towards continuous capture or archival of personal experience [35], for example, using video glasses like eyeTap [41] or eyeBlog [17] (see Fig. 6.4).

'Blogging has become a convenient tool to notify others of what is happening in one's life. Accessed through the http:// protocol, 'Blogs are particularly convenient as data communication tools, since the only technical requirement to view a blog is

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Figure 6.4: Continuous archival of personal experiences using eyeBlog video glasses [17].

an internet browser which happens to exist on many ubiquitous computing devices. However, as we discussed earlier, for the most part current 'blogging technology does not provide *internal* insight into the mind of the user.

6.3.2 'Plog: Physiological Weblog

Unlike other blogging technologies, the Physiological Weblog, or 'Plog for short, provides *internal* experiential information about the user. The 'Plog makes use of the interruptability model developed earlier as part of an automated availability status system that weblogs the users physiological state, as well as their predicted interruptability (see Figure 6.5). The Physiological Weblog provides a web–based interface to allow online users to assess the availability of mobile users, while also being able to browse the *internal* physiological state user hooked into the system.

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The 'Plog was made possible by a flexible PAUI architecture (see Figure 6.2) which allowed for system calls that called the appropriate resources to continuously transfer the physiological data and interruptability level to a remote server, in close to real–time.

6.3.3 'Plog: System Description

The Physiological Weblog, or 'Plog, continuously archives physiological data, and correlates this data with a model of interruptability. 'Plog continuously uploads physiological data information to a web server through a secure ssh protocol [8] accessed through the PAUI architecture. Typically this physiological information includes graphical plots of the ECG or EMG, along with various physiological measures such as heart–rate and muscle activity. The 'Plog then displays this physiological information to others, along with a simple interface that communicates the user's exact interruptability to others, using a scale from one to five. This feature allows others to immediately know the interruptability of the user, without having to interpret the physiological data, thus facilitating informed decisions on availability prior to communications.

Preliminary trials of the Plog system have proved promising, and the continuous update of physiological and attentive data has been well received by both the users of the system and those others that are trying to reach them.

6.3.4 Discussion

The most important function of the 'Plog is the *communication* of attention which allows for an alternative approach to regulating interruptions. Unlike the PAUI Cell

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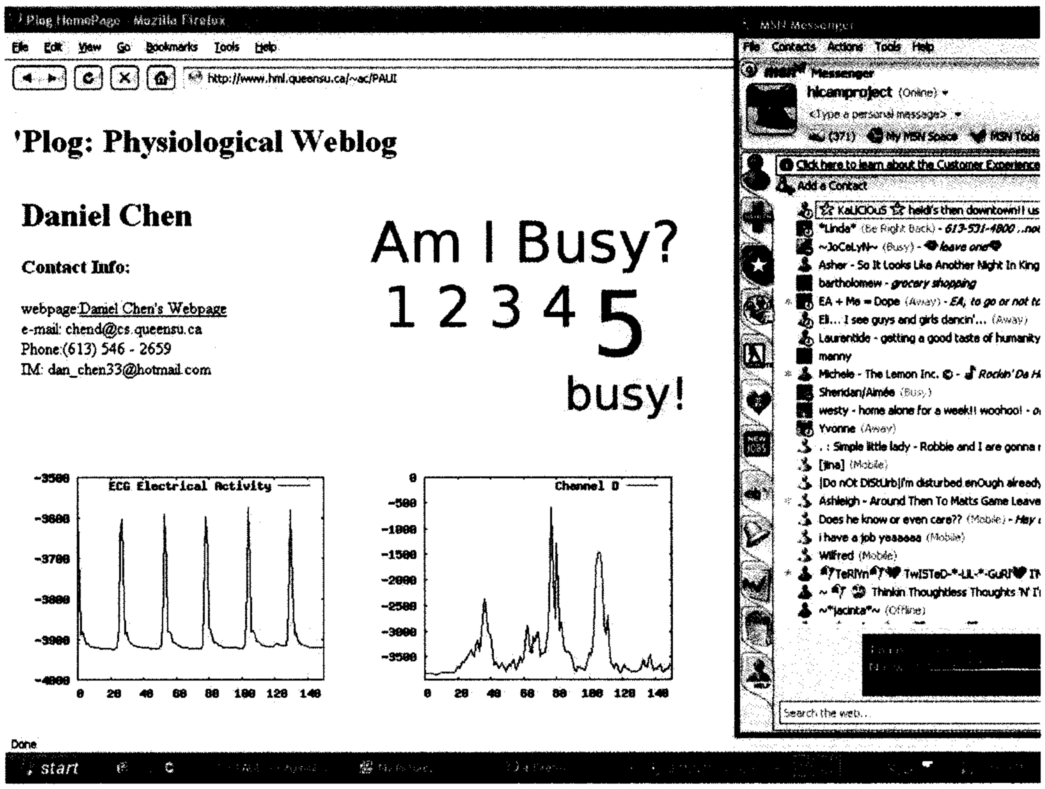

Figure 6.5: The physiological weblog or Plog, displaying the predicted level of interruptability of a user.

phone's approach of directly regulating interruptions, the number of interruptions is *self-mediated* by others who are forced to become more considerate of the user's current availability. As such, it is expected that 'Plog will act as an attentive notice board that could reduce the number of inopportune interruptions by emails, instant messages or telephone calls. In the future, it would be valuable to formally evaluate the effectiveness of the 'Plog as a means to communicate user availability and to consequently reduce interruptions. However, applications such as the 'Plog do raise the potential privacy concerns, when revealing a user's internal physiology information

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on the world wide web.

In this chapter we have discussed the two applications of the PAUI concept, the PAUI Cell phone and the 'Plog. Although they each may take different approaches, the PAUI Cell Phone and the 'Plog are just two illustrations of the possibilities in using PAUIs to reduce the interruptions that overwhelm their users.

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Chapter 7

Summary and Conclusions

7.1 Summary

This thesis addressed the problem of overwhelming interruptions created by ubiquitous computing devices through the concept of Physiologically Attentive User Interfaces (PAUIs). PAUIs were presented as a novel means to help regulate or mediate interruptions. In order to realize this goal, contributions were made to areas of HCI including the modeling of interruptability and Attentive User Interfaces.

7.1.1 Contribution to the Modeling of Interruptability

An important aspect addressed in this thesis was the use of *internal* metrics to model interruptability versus *external* metrics. Previous approaches based themselves on physical sensors that could only quantify overt physical activity, and modeled the user's interruptability based upon some presumed task. However, mental engagement is inherently *covert* and can not be quantified with such sensors.

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This thesis made novel use of physiological sensors which do measure the *internal* state of the user, to model interruptability. Although a classifier approach was initially taken, an empirical physiological model of interruptability was finally realized that could predict interruptability well. Based upon using the HRV and EMG physiological measures in an empirical user study, a linear model was created for each participant based upon their individual data. The results of these experiments showed that the average correlation of the linear model with the user's data was r=0.39, and r2=0.226, meaning that 22.6% of the variance could be predicted by the model. Considering the modest number of participants in this study, the results are promising.

The empirical physiological model of interruptability is important in a number of ways. Firstly, since it does not depend on external metrics it is not subject to external sensor noise. Secondly, since it is based upon the user's inherent internal physiological metrics (that reflect mental engagement) it is independent of the task the user is performing.

7.1.2 Contribution to Attentive User Interfaces

Based upon the previous contribution of a physiological model of attention, it became possible to develop applications around the novel area of Physiological Attentive User Interfaces (PAUIs). Previously, Attentive User Interfaces (AUIs), based themselves on sensing overt characteristics of user attention, such as eye contact. By making these interfaces physiologically responsive, AUIs no longer need to depend only on external measures that do not reflect the user's actual mental engagement or attentive state. As such, Physiologically Attentive User Interfaces (PAUIS) extend the area of AUIs.

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This thesis presented the first developed PAUI applications, the PAUI Cell Phone and the Physiological Weblog or 'Plog. Both applications illustrate how PAUIs can mediate or regulate the interruptions that reach a user, in a way similar to mediated reality discussed in Chapter 2. The PAUI Cell phone takes the direct approach of allowing or blocking incoming interruptions or notifications using the PAUI classifier. Meanwhile, the Physiological Weblog or 'Plog, used our empirical physiological model of interruptability to automatically communicate the user's current availability status to others through an updated webpage. By *communicating* the user's level of interruptability to others, the Plog reduced interruptions by allowing others to know when or when it is not appropriate contact the user.

7.2 Future Work

This thesis opens some interesting avenues for future research. To further expand the scope of this thesis, the following points could be considered:

- **Other physiological signals could be explored that may contribute to the user's interruptability model.** In our study the Procomp+ [3] device provided Skin Conductance (SC), and Blood Volume Pressure (BVP) sensors which specifically made their measurements from the finger tips. However, it was found that these finger tip based sensors were intrusive, and also subject to noise because they moved around when the user performed most tasks. There are, however, sensors on the market that are not finger tip based, and worth exploring.

- **The nature of the experimental study could be expanded to include**

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more users from a larger demographic pool. Although the experiment yielded some interesting results, they were limited to a specific demographic of younger users. It would be valuable to see how well these experimental models hold up when applied to a broader cross section of the population. In future experiments, it would be useful to include younger and older users, of varying degrees of experience with technology.

- **A number of novel applications which use physiological interruptability models could be developed.** In this thesis, the 'Plog communicated the interruptability of the user to others via a web log. However, the knowledge of a users particular level of interruptability can be more generally useful. Another possible application would be to continuously archive the interruptability data of a user to track how the interruptability varied during the day. This would be useful for managing tasks and workflow in office environments.

Although there are many potential areas for future work, it is important to make ethical considerations along the way. By accessing physiological data that is intrinsic to the user's internal characteristics, some privacy considerations may need to follow. For example, future application developers must understand the personal implications of making physiological based user data available to others, and how it could effect the users life if such information was available to employers, friends, family or anybody on the web. In the case of employers, it could be conceivable one day that bosses could request to have intimate knowledge of a user's productivity based upon their interruptability data.

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7.3 Conclusion

By using *internal* physiological measures of a user's internal state, this thesis demonstrated it is possible to model a user's interruptability independent of whatever task they are currently performing.

Based upon this physiological modeling of attention, it becomes possible to create interfaces which are physiologically responsive to the user's attentive state. In this thesis, a number of applications were created which demonstrate the feasibility of creating Physiologically Attentive User Interfaces (PAUIs)

PAUIs can function in close proximity to users, and address the problem of managing overwhelming interruptions from ubiquitous devices. To accomplish this, PAUIs mediate or regulate the interruptions that constantly bombard users from ubiquitous computing devices. As such, PAUIs can play an important role in helping users overcome the information overload of our increasingly technology based society.

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