Physiological Computing: Interfacing with the Human Nervous System

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Abstract

This chapter describes the physiological computing paradigm where electrophysiological changes from the human nervous system are used to interface with a computer system in real time. Physiological computing systems are categorized into five categories: muscle interfaces, brain-computer interfaces, biofeedback, biocybernetic adaptation and ambulatory monitoring. The differences and similarities of each system are described. The chapter also discusses a number of fundamental issues for the design of physiological computing system, these include: the inference between physiology and behaviour, how the system represents behaviour, the concept of the biocybernetic control loop and ethical issues.

1. Introduction

Communication with computers is accomplished via a standard array of input devices requiring stereotypical actions such as key pressing, pointing and clicking. At the time of writing, the standard combination of keyboard/mouse is starting to yield to intuitive physical interfaces (Merrill & Maes, 2007), for instance, the Nintendo Wii and forthcoming "whole-body" interfaces such as Microsoft's Project Natal. Traditionally the physicality of human-computer interaction (HCI) has been subservient to the requirements of the input devices. This convention is currently in reversal as computers learn to understand the signs, symbols and gestures with which we physically express ourselves to other people. If users can communicate with technology using overt but natural hand gestures, the next step is for computers to recognise other forms of spontaneous human-human interaction, such as eye gaze (Wachsmuth, Wrede, & Hanheide, 2007), facial expressions (Bartlett, Littlewort, Fasel, & Morvellan, 2003) and postural changes (Ahn, Teeters, Wang, Breazeal, & Picard, 2007). These categories of expression involve subtle changes that are not always under conscious control. In one sense, these kinds of signals represent a more intuitive form of HCI compared to overt gesture because a person may communicate her needs to a device with very little intentionality. However, changes in facial expression or body posture remain overt and discernible by close visual observation. This progression of intuitive body interfaces reaches a natural conclusion when the user communicates with a computer system via physiological changes that occur under the skin. The body emits a wide array of bio-electrical signals, from increased muscle tension to changes in heart rate to tiny fluctuations in the electrical activity of the brain. These signals represent internal channels of communication between various components of human central nervous systems. These signals may also be used to infer behavioural states, such as exertion during exercise, but their real potential to innovate HCI lies in the ability of these measures to capture psychological processes and other dimensions that remain covert and imperceptible to the observer.

There is a long literature in the physiological computing tradition inspired by work on affective computing (Picard, 1997), specifically the use of psychophysiology to discern different emotional states and particularly those negative states such as frustration (Kapoor, Burleson, & Picard, 2007) that both designer and user wish to minimise or avoid. A parallel strand of human factors research (Pope, Bogart, & Bartolome, 1995; Prinzel, Parasuraman, et al., 2003) has focused on the detection of mental engagement using electroencephalographic (EEG) measures of brain activity. The context for this research is the development of safe and efficient cockpit automation; see Scerbo, Freeman, & Mikulka (2003) for summary of automation work and Rani & Sarkar (2007) for similar approach to interaction with robots. The same approach was adopted to monitor the mental workload of an operator in order to avoid peaks (i.e. overload) that may jeopardise safe performance (Wilson & Russell, 2003; 2007). In these examples, psychophysiology is used to capture levels of cognitive processing rather than emotional states. Psychophysiology may also be used to quantify those motivational states underlying the experience of entertainment technology (Mandryk, Inkpen, & Calvert, 2006; Yannakakis, Hallam, & Hautop Lund, 2007). This application promotes the concept of adaptive computer games where software responds to the state of the player in order to challenge or help the individual as appropriate (Dekker & Champion, 2007; Fairclough, 2007; Gilleade

& Dix, 2004). Specific changes in psychophysiology may also be used as an intentional input control to a computer system, Brain-Computer Interfaces (BCI) (Allison, Wolpaw, & Wolpaw, 2007; Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002) involve the production of volitional changes in EEG activity in order to direct a cursor and make selections in a manner similar to mouse movement or a key press.

Psychophysiology has the potential to quantify different psychological states (e.g. happiness vs. frustration), to index state changes along a psychological continuum (e.g. low vs. high frustration) and to function as a proxy for input control (e.g. a BCI). Psychophysiological data may also be used to identify stable personality traits, such as motivational tendencies (Coan & Allen, 2003) and predispositions related to health, such as stress reactivity (Cacioppo, et al., 1998). The diversity and utility of psychophysiological monitoring provides ample opportunity to innovate HCI but what kinds of benefits will be delivered by a new generation of physiological computing systems? The first advantage is conceptual, contemporary human-computer communication has been described asymmetrical in the sense that the user can obtain a lot of information about the system (e.g. hard disk space, download speed, memory use) while the computer is essentially 'blind' to the psychological status of the user (Hettinger, Branco, Encarnaco, & Bonato, 2003). The physiological computing paradigm provides one route to a symmetrical HCI where both human and computer are capable of "reading" the status of the other without the requirement for the user to produce explicit cues; this symmetrical type of HCI can be described as a dialogue as opposed to the asymmetrical variety that corresponds to two monologues (Norman, 2007). One consequence of symmetrical HCI is that technology has the opportunity to demonstrate "intuition" or "intelligence" without any need to overtly consult the user. For example, a physiological computing system may offer help and advice based upon a psychophysiological diagnosis of frustration - or make a computer game more challenging if a state of boredom is detected. Given that the next generation of 'smart' technology will be characterised by qualities such as increased autonomy and adaptive capability (Norman, 2007), future systems must be capable of responding proactively and implicitly to support human activity in the workplace and the home, e.g. ambient intelligence (Aarts, 2004). As technology develops in this direction, the interaction between users and machines will shift from a master-slave dyad towards the kind of collaborative, symbiotic relationship (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004) that requires the computer to extend awareness of the user in real-time.

Each interaction between user and computer is unique at some level, the precise dynamic of the HCI is influenced by a wide range of variables originating from the individual user, the status of the system or the environment. The purpose of dialogue design is to create an optimal interface in order to maximise performance efficiency or safety, which represents a tacit attempt to "standardise" the dynamic of the HCI. Similarly, human factors and ergonomics research has focused on the optimisation of HCI for a generic 'everyman' user. Physiological computing represents a challenge to the concepts of a standard interaction or a standard user. Interaction with a symmetrical physiological computing system incorporates a reflexive, improvisatory element as both user and system respond to feedback from the other in real-time. There may be benefits associated with this real-time, dynamic adaptation such as the process of individuation (Hancock, Pepe, & Murphy, 2005) where the precise response of the system is tailored to the unique skills and preferences of each user, e.g. (Rashidi & Cook, in press). As the individual develops an accurate model of system contingencies and competencies and vice versa, human-computer coordination should grow increasingly fluid and efficient. For example, certain parameters of the system (e.g. the interface) may change as the person develops from novice to experienced user, e.g. acting with greater autonomy, reducing the frequency of explicit feedback. This reciprocal human-machine coupling is characterised as a mutual process of co-evolution with similarities to the development of human-human relationships in teamwork (Klein, et al., 2004). Central to this idealised interaction is the need to synchronise users' models of system functionality, performance characteristics etc. with the model of user generated by the computer system with respect to preferences, task context and task environment. In this way, physiological computing shifts the dynamic of the interaction from the generic to the specific attributes of the user. This shift is "directed to explore ways through which each and every individual can customize his or her tools to optimize the pleasure and efficiency of his or her personal interaction" (Hancock, et al., 2005) (p. 12).

Traditional input devices required a desktop space for keyboard or mouse that effectively tied HCI to a specific "office" environment. The advent of mobile communication devices and lightweight notebooks/laptops has freed the user from the desktop but not from the ubiquity of the keyboard or touchpad. The development of unintrusive, wearable sensors (Baber, Haniff, & Woolley, 1999; Picard & Healey, 1997; Teller, 2004) offers an opportunity for users to communicate with ubiquitous technology without any overt input device. A psychophysiological representation of the user state could be collected unobtrusively and relayed to personal devices located on the person or elsewhere. Unobtrusive monitoring of physiology also provides a means for users to overtly communicate with computers whilst on the move or away from a desktop. The development of muscle-computer interfaces (Saponas, Tan, Morris, & Balakrishnan, 2008) allows finger movements to be monitored and distinguished on potentially any surface in order to provide overt input to a device. Data collection from wearable sensors could be used to monitor health and develop telemedicine-related applications (Kosmack Vaara, Hook, & Tholander, 2009; Morris & Guilak, 2009) or to adapt technology in specific ways, e.g. if the user is asleep, switch all messages to voicemail. With respect to system adaptation, this "subconscious" HCI (i.e. when a device adapts to changes in user state without any awareness on the part of the user) could be very useful when the user is eyes- or hands-busy, such as driving a car or playing a computer game. This utilisation of the approach in this scenario allows physiological computing to extend the communication bandwidth of the user.

The potential benefits of physiological computing are counteracted by significant risks associated with the approach. The inference from physiological change to psychological state or behaviour or intention is not straightforward (Cacioppo, Tassinary, & Berntson, 2000). Much of the work on the psycho-physiological inference (i.e. the way in which psychological significance is attached to patterns of physiological activity) has been conducted under controlled laboratory conditions and there is a question mark over the robustness of this inference in the field, i.e. psychophysiological changes may to be small and obscured by gross physical activity or environmental factors such as temperature. It is important that physiological computing applications are based upon a robust and reliable psychophysiological inference in order to work well. The physiological computing paradigm has the potential to greatly increase the complexity of the HCI which may be a risk in itself. If a physiological computing application adapts functionality or interface features in response to changes in the state of the user, this dynamic adaptation may be double-edged. It is hoped that this complexity may be harnessed to improve the quality of the HCI in terms of the degree of "intelligence" or "anticipation" exhibited by the system. However, the relationship between system complexity and compatibility with the user is often negative, i.e. the higher the complexity of the system, the lower the level of compatibility (Karwowski, 2000). Therefore, the complex interaction dynamic introduced by physiological computing devices has the potential to dramatically degrade system usability by increasing the degree of confusion or uncertainty on the part of the user. Finally, physiological computing approaches are designed to use physiology as a markers of what are often private, personal experiences. Physiological computing technologies cross the boundary between overt and covert expression, in some cases capturing subtle psychological changes of which the users may be unaware. This kind of technology represents a threat to privacy both in the sense of data security and in terms of feedback at the interface in a public space.

The aim of the current chapter is to describe different categories of physiological computing systems, to understand similarities and differences between each type of system, and to describe a series of fundamental issues that are relatively common to all varieties of physiological computing applications.

2. Categories of Physiological Computing

A physiological computing system is defined as a category of technology where electrophysiological data recorded directly from the central nervous system or muscle activity are used to interface with a computing device. This broad grouping covers a range of existing system concepts, such as Brain-Computer Interfaces (Allison, et al., 2007), affective computing (Picard, 1997) and ambulatory monitoring (Ebner-Priemer & Trill, 2009). This definition excludes systems that classify behavioural change based on automated analysis of gestures, posture, facial expression or vocal characteristics. In some cases, this distinction merely refers to the method of measurement rather than the data points themselves; for example, vertical and horizontal eye movement may be measured directly from the musculature of the eye via the electrooculogram (EOG) or detected remotely via eye monitoring technology where x and y coordinates of gaze position are inferred from tracking the movement of pupil.

Figure 1 (below) describes a range of physiological computing systems that are compared and contrasted with overt input control derived from conventional keyboard/mouse or gesture-based control [1]. The second category of technology describes those physiological computing concepts where input control is based upon muscular activity [2]. These systems include cursor control using eye movements (Tecce, Gips, Olivieri, Pok, & Consiglio, 1998) or gaze monitoring (Chin, Barreto, Cremades, & Adjouadi, 2008) or eye blink activity (Grauman, Betke, Gips, & Bradski, 2001). Muscle interfaces have traditionally been explored to offer alternative means of input control for the people with disabilities and the elderly (Murata, 2006). The same "muscle-interface" approach using electromyographic (EMG) activity has been used to capture different hand gestures by monitoring the muscles of the forearm (Saponas, et al., 2008), facial expressions (Huang, Chen, & Chung, 2006) and subvocal speech (Naik, Kumar, & Arjunan, 2008). Brain-Computer Interfaces (BCI) [3] are perhaps the best known variety of physiological computing system. These systems were originally developed for users with profound disabilities (Allison, et al., 2007; Wolpaw, et al., 2002) and indexed significant changes in the electrical activity of the cortex via the electroencephalogram (EEG), e.g. evoked-potentials (ERPs), steady state visual evoked potentials (SSVEPs). Several arguments have been forwarded to promote the use of BCI by healthy users (Allison, Graimann, & Graser, 2007), such as novelty or to offer an alternative mode of input for the 'hands-busy' operator. Zander & Jatzev (2009) distinguished between active BCI systems that rely on direct EEG correlates of intended action (e.g. changes in the somatosensory cortex in response to motor imagery) and reactive BCI where EEG activity is not directly associated with output control (e.g. use of P300 ERP amplitude to a flashing array of letters to enable alphanumeric input). Biofeedback systems [4] represent the oldest form of physiological computing. The purpose of this technology is to represent the physiological activity of the body in order to promote improved self-regulation (Schwartz & Andrasik, 2003). This approach has been applied to a range of conditions, such as asthma, migraines, attentional deficit disorder and as relaxation therapy to treat anxiety-related disorders and hypertension. Biofeedback therapies are based on monitoring the cardiovascular system (e.g. heart rate, blood pressure), respiratory variables (e.g. breathing rate, depth of respiration), EMG activity, and EEG (i.e. neurofeedback) and training users to develop a degree of volitional control over displayed physiological activity. The concept of biocybernetic adaptation [5] was developed by Pope, et al. (1995) to describe a adaptive computer system that responded to changes in EEG activity by controlling provision of system automation (Freeman, Mikulka, Scerbo, & Scott, 2004; Prinzel, Freeman, Scerbo, Mikulka, & Pope, 2003). This types of system monitor naturalistic changes in the psychological state of the person, which may be related to variations in cognitive workload (Wilson & Russell, 2003) or motivation and emotion (Mandryk & Atkins, 2007; Picard, Vyzas, & Healey, 2001). This approach has been termed "wiretapping" (Wolpaw, et al., 2000) or passive BCI (Zander & Jatzev, 2009). In essence, the psychological status of the user is monitored in order to trigger software adaptation that is both timely and intuitive (Fairclough, 2009). The final category of technology concerns the use of unobtrusive wearable sensors that monitor physiological activity over a sustained period of days or months. These ambulatory systems [6] may be used to monitor emotional changes (Picard & Healey, 1997; Teller, 2004) or health-related variables (McFetridge-Durdle, Routledge, Parry, Dean, & Tucker, 2008; Milenkovic, Otto, & Jovanov, 2006). These systems may trigger feedback to the individual from a mobile device when "unhealthy" changes are detected (Morris, 2007) or the person may review personal data on a retrospective basis (Kosmack Vaara, et al., 2009).

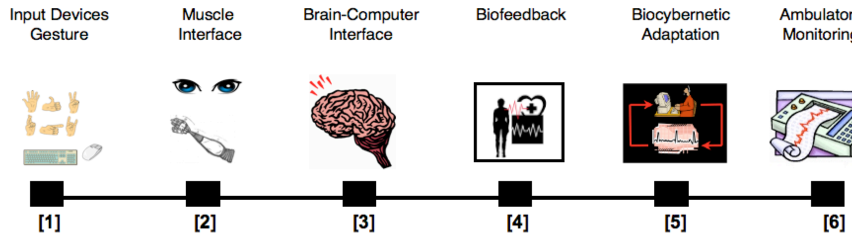

Figure 1. Five categories of physiological computing systems

The biocybernetic loop is a core concept for all physiological computing systems (Fairclough & Venables, 2004; Pope, et al., 1995; Prinzel, Freeman, Scerbo, Mikulka, & Pope, 2000) with the exception of some forms of ambulatory monitoring [6]. This loop corresponds to a basic translational module that transforms physiological data into a form of computer control input in real-time. The loop has at least three distinct stages: (1) signal acquisition, filtering and digitization, (2) artifact correction and the extraction of relevant features and (3) the translation of an attenuated signal into output for computer control. The precise form of the mapping between physiological change and control output will differ from system to system; in some cases, it is relatively literal and representative, e.g. the relationship between eye movements and x,y coordinates in space. Other systems involve a symbolic mapping where physiological activity is converted into a categorization scheme that has psychological meaning. For example, the relationship between autonomic activity and emotional states falls into this category (Mandryk & Atkins, 2007), similarly the mapping between EEG activity and mental workload (Gevins, et al., 1998; Grimes, Tan, Hudson, Shenoy, & Rao, 2008) or the way in which respiratory data may be represented as sound or visual animation via a biofeedback interface. These mappings have been developed primarily to produce one-dimensional output, although there are two-dimensional examples of both BCI (Wolpaw & McFarland, 2004) and biocybernetic adaptation (Rani, Sims, Brackin, & Sarkar, 2002). Sensitivity gradation is a common issue for many biocybernetic loops. Some forms of BCI and all forms of biocybernetic adaptation rely on an attenuated signal for output, for example, a steady and gradual increase over a specified time window. In the case of ambulatory monitoring, some systems alert the user to "unhealthy" physiological activity use the same kind of sensitivity gradation to trigger an alert or diagnosis. Those ambulatory systems that do not incorporate a biocybernetic loop are those that rely exclusively on retrospective data, such as the affective diary concept (Kosmack Vaara, et al., 2009); in this case, real-time data is simply acquired, digitised, analysed and conveyed to the user in various formats without any translation into computer control.

The five categories of physiological computing system illustrated in Figure 1 have been arranged to emphasise important differences and similarities. Like conventional input via keyboard and mouse, it is argued that muscle interfaces involving gestures, facial expressions or eye movements are relatively overt and visible to an observer. The remaining systems to the right of the diagram communicate with computer technology via covert changes in physiological activity. When a user communicates with a computer via keyboard/mouse [1], muscle interface [2] or BCI [3], we assume these inputs are intentional in the sense that the user wishes to achieve a specific action. The use of a Biofeedback system [4] is also volitional in the sense that the person uses the interface in order to manipulate or self-regulate a physiological response. By contrast, Biocybernetic Adaptation [5] involves monitoring spontaneous physiological activity in order to represent the state of the user with respect to a specific psychological dimension, such as emotion or cognitive workload. This is an unintentional process during which the user essentially remains passive (Fairclough, 2007, 2008). The same is true of ambulatory monitoring systems [6] that conform to the same dynamic of user passivity. Muscle Interfaces [2], BCIs [3] and biofeedback [4] all operate with continuous feedback. Both Muscle Interfaces and BCIs are analogous to command inputs such as keystrokes, discrete gestures or mouse movements; these devices require continuous feedback in order to function. Biofeedback systems also rely on continuous feedback to provide users with the high-fidelity of information necessary to manipulate the activity of the central nervous system. In this case, the computer interface is simply a conduit that displays physiological activity in an accessible form for the user. Those physiological computing systems described as Biocybernetic Adaptation [5] rely on a different dynamic where feedback may be presented in a discrete form. For example, adaptive automation systems may signal a consistent trend, such as increased task engagement over a period of seconds or minutes, by activating an auto-pilot facility (Prinzel, Pope, & Freeman, 2002); similarly, a computer learning environment could signal the detection of frustration by offering help or assistance to the user (Burleson & Picard, 2004; Gilleade, Dix, & Allanson, 2005). The contingencies underlying this discrete feedback may not always be transparent to the user; in addition, discrete feedback may be delayed in the sense that it represents a retrospective trend. Ambulatory Monitoring systems [6] are capable of delivering relatively instant feedback or reflecting a data log of hours or days. In the case of ambulatory systems, much depends on why these data are recorded. Ambulatory recording for personal use tends to fall into two categories: (1) quantifying physiological activity during specific activities such as jogging and (2) capturing physiological activity for diary or journal purposes. In the case of the former, feedback is delivered in high fidelity (e.g. one reading every 15 or 30sec), whereas journal monitoring may aggregate data over longer time windows (e.g. one reading per hour).

The biocybernetic control loop serves a distinct purpose when physiology is used as an explicit channel for communication with a computing device, e.g. muscle interface [2], BCI [3]. In these cases, physiological activity is translated into analogues of distinct actions, to activate a function or identify a letter or move a cursor through two-dimensional space. Biocybernetic Adaptation [5] is designed to mediate an implicit interaction between the status of the user and the meta-goals of the HCI (Fairclough, 2008). The latter refers to the design goals of the technological device; in the case of an adaptive automation system, the meta-goals are to promote safe and efficient performance; for a computer game, the goal would be to entertain and engage. Biocybernetic Adaptation [5] provides the opportunity for real-time adjustment during each interaction in order to reinforce the design goals of the technology. Finally, there may be a requirement for training when physiology is used as a means of explicitly computer control. Muscle-based interaction [2] may require some familiarisation as user adjust to the sensitivity of system response. BCI devices [3] are often associated with a training regime, although there is evidence that their training requirements may not be particularly onerous (Guger, Edlinger, Harkam, Niedermayer, & Pfurtscheller, 2003). Biofeedback systems [4] are designed as a training tool for self-regulation. However, physiological computing systems that rely on implicit communication such as Biocybernetic Adaptation [5] and Ambulatory Monitoring [6] have no training requirement from the perspective of the user.

The continuum of physiological computing systems illustrated in Figure 1 obscures the huge overlap between different categories. Ambulatory monitoring [6] represents a common denominator for all other physiological computing systems, i.e. if a system records electrophysiological activity from the user, these data can also be used for affective diaries or health monitoring. In addition, it is anticipated that wearable sensors currently associated with ambulatory monitoring will become the norm for all physiological computing systems in the future. A biofeedback component [4] is also ubiquitous across all systems. Users of Muscle Interfaces [2] and BCIs [3] rely on feedback at the interface in order to train themselves to produce reliable gestures or consistent changes in EEG activity. In these cases, the success or failure of a desired input control represents a mode of biofeedback. Biocybernetic Adaptation [5] may also include an element of biofeedback; these systems monitor implicit changes in psychophysiology in order to adapt the interface, but if these adaptations are explicit and consistently associated with distinct physiological changes, then changes at the interface will function as a form of biofeedback. Furthermore, if the user of a Biocybernetic Adaptation system [5] learns how to self-regulate physiology via biofeedback [4], this opens up the possibility of volitional control (over physiology) to directly and intentionally control system adaptation; in this case, the Biocybernetic Adaptation system [5] may be operated in the overt, intentional mode normally used to characterise Muscle Interfaces [2] and BCI [3]. There are a number of system concepts already available that combine Ambulatory Monitoring [6] with Biofeedback [4]; for instance, the Home Heart system (Morris, 2007) that monitors stress-related cardiovascular changes and triggers a biofeedback exercise as a stress countermeasure.

By breaking down the distinction between different types of physiological computing system in Figure 1, we may also consider hybrid systems that blend different modes of input control and system adaptation. For example, it is difficult to imagine BCI technology being attractive to healthy users because of its limited bandwidth, e.g. two degree of spatial freedom, or two-choice direct selection. A hybrid system where BCI is used alongside a keyboard, mouse or console appears a more likely option, but the design of such a system faces two primary obstacles (Allison, et al., 2007): (1) assigning functionality to the BCI that is intuitive, complimentary and compatible with other input devices, and (2) limitations on human information processing in a multi-tasking framework. The multiple-resource model (Wickens, 2002) predicts that control via BCI may distract attention from other input activities via two routes: sharing the same processing code (spatial vs. verbal) or by demanding attention at an executive or central level of processing. However, there is evidence that these types of time-sharing deficits may be overcome by training (Allison, et al., 2007). The combination of Muscle Interfaces and BCI may work well for hands-free locate-and-select activities such as choosing from an array of images; eye movement may be used to locate the desired location in space and a discrete BCI trigger from the EEG used to make a selection. Biocybernetic Adaptation may be combined with either Muscle Interfaces or BCI because the former operate at a different level of the HCI (Fairclough, 2008). A system that trained users how to operate a Muscle Interface or a BCI could incorporate a biocybernetic adaptive element whereby the system offered help or advice based on the level of stress or workload associated with the training programme. Similarly, Biocybernetic Adaptation may be combined with conventional controls or gesture input to operate as an additional channel of communication between user and system. Those physiological computing systems such as Biocybernetic Adaptation or Ambulatory Monitoring that emphasise monitoring of behavioural states could also be combined with sensors that detect overt changes in facial expression, posture or vocal characteristics to create a multi-modal representation of the user, e.g. Kapoor, et al. (2007).

Physiological computing systems may be described along a continuum from overt and intentional input control with continuous feedback to covert and passive monitoring systems that provide feedback on a discrete basis. There is a large overlap between distinct categories of physiological computing systems and enormous potential to use combinations or hybrid versions.

3. Fundamental Issues

The development of physiological computing remains at an early stage and research efforts converge on several fundamental issues. The purpose of this section is to articulate issues that have a critical bearing on the development and evaluation of physiological computing systems.

3.1 The Psychophysiological Inference

The complexity of the psychophysiological inference (Cacioppo & Tassinary, 1990; Cacioppo, Tassinary, & Berntson, 2000b) represents a significant obstacle for the design of physiological computing systems. The rationale of the biocybernetic control loop is based on the assumption that the psychophysiological measure (or array of measures) is an accurate representation of a relevant psychological element or dimension, e.g. hand movement, frustration, task engagement. This assumption is often problematic because the relationship between physiology and psychology is inherently complex. Cacioppo and colleagues (1990; 2000) described four possible categories of relationship between physiological measures and psychological elements:

- One-to-one (i.e. a physiological variable has a unique isomorphic relationship with a psychological or behavioural element)
- Many-to-one (i.e. two or more physiological variables are associated with the relevant psychological or behavioural element)
- One-to-many (i.e. a physiological variable is sensitive to one or more psychological or behavioural elements)
- Many-to-many (i.e. several physiological variables is associated with several psychological or behavioural elements)

The implications of this analysis for the design of physiological computing systems should be clear. The one-to-many or many-to-many categories that dominate the research literature represent psycho-physiological links that are neither exclusive nor uncontaminated. This quality is captured by the diagnosticity of the psychophysiological measure, i.e. the ability of the measure to target a specific psychological concept or behaviour and remain unaffected by related influences (O'Donnell & Eggemeier, 1986). In the case of Muscle Interfaces, it is assumed that one-to-one mapping between physiology and desired output may be relatively easy to obtain, e.g. move eyes upwards to move cursor in desired direction. For other systems such as BCI and particularly biocybernetic adaptation, finding a psychophysiological inference that is sufficiently diagnostic may be more problematic. Whilst it is important to maximise the diagnosticity of those measures underlying a physiological computing system, it is difficult to translate this general requirement into a specific guideline. Levels of diagnostic fidelity will vary for different systems. The system designer must establish the acceptable level of diagnosticity within the specific context of the task and the system.

3.2 The Representation of Behaviour

Once psychophysiological inference has been established, the designer may consider how specific forms of reactivity (e.g. muscle tension, ERPs) and changes in the psychological state of the user should be operationalised by the system. This is an important aspect of system design that determines:

- the transfer dynamic of how changes in muscle tension translate into movement of a cursor for a muscle interface
- the relationship between activity in the sensorimotor cortex and output to wheelchair control for a BCI
- the relationship between changes in EEG and autonomic activity and the triggering of adaptive strategies during biocybernetic adaptation

The biocybernetic loop encompasses the decision-making process underlying software adaptation. In its simplest form, these decision-making rules may be expressed as simple Boolean statements; for example, IF frustration is detected THEN offer help. The loop incorporates not only the decision-making rules, but in the case of Biocybernetic Adaptation, the psychophysiological inference implicit in the quantification of those trigger points used to activate the rules. In our study (Fairclough, Venables, & Tattersall, 2006) for example, this information took the form of a linear equation to represent the state of the user, e.g. subjective mental effort = x_1 * respiration rate – x_2 * eye blink frequency + intercept, as well as the quantification of trigger points, e.g. IF subjective effort > y THEN adapt system. Other studies have also used linear modelling techniques and more sophisticated machine learning approaches systems to characterise user state in terms of the psychophysiological response, e.g. (Liu, Rani, & Sarkar, 2005; Mandryk & Atkins, 2007; Rani, et al., 2002; Wilson & Russell, 2003).

The psychological state of the user has been represented as a one-dimensional continuum, e.g. frustration (Gilleade & Dix, 2004; Kapoor, et al., 2007; Scheirer, Fernandez, Klein, & Picard, 2002), anxiety (Rani, Sarkar, & Liu, 2005), task engagement (Prinzel, et al., 2000), mental workload (Wilson & Russell, 2007). Other research has elected to represent user state in terms of: distinct categories of emotion (Healey & Picard, 1997; Lisetti & Nasoz, 2004; Lisetti, Nasoz, LeRouge, Ozyer, & Alvarez, 2003), two-dimensional space of activation and valence (Kulic & Croft, 2005, 2006) and distinct emotional categories based upon a two-dimensional analysis of activation and valence (Mandryk & Atkins, 2007) As stated earlier, reliance on a one-dimensional representation of the user may restrict the range of adaptive options available to the system. This may not be a problem for some systems, but complex adaptation requires a more elaborated representation of the user in order to extend the repertoire of adaptive responses.

Early examples of physiological computer systems will rely on one-dimensional representations of the user, capable of relatively simple adaptive responses. The full potential of the technology may only be realized when systems are capable of drawing from an extended repertoire of precise adaptations, which will require complex representations of user behaviour or state in order to function.

3.3 The Biocybernetic Control Loop

The design of a physiological computing system is based upon the biocybernetic control loop (Fairclough & Venables, 2004; Pope, et al., 1995; Prinzel, et al., 2000). The biocybernetic loop defines the modus operandi of the system and is represented as a series of contingencies between psychophysiological reactivity and system responses or adaptation. These rules are formulated to serve a meta-goal or series of meta-goals to provide the system with a tangible and objective rationale. The meta-goals of the biocybernetic loop must be carefully defined and operationalised to embody generalised human values that protect and enfranchise the user (Hancock, 1996). For example, the physiological computing system may serve a preventative meta-goal, i.e. to minimise any risks to the health or safety of the operator and other persons. Alternatively, meta-goals may be defined in a positive way that promotes pleasurable HCI (Hancock, et al., 2005; Helander & Tham, 2003) or states of active engagement assumed to be beneficial for both performance and personal well-being.

The biocybernetic loop is equipped with a repertoire of behavioural responses or adaptive interventions to promote the meta-goals of the system, e.g. to provide help, to give emotional support, to manipulate task difficulty (Gilleade, et al., 2005). The implementation of these interventions is controlled by the loop in order to 'manage' the psychological state of the user. Correspondingly, the way in which person responds to each adaptation is how the user 'manages' the biocybernetic loop. This is the improvisatory crux that achieves human-computer collaboration by having person and machine respond dynamically and reactively to responses from each other. It may be useful for the loop to monitor how users respond to each intervention in order to individualise (Hancock, et al., 2005) and refine this dialogue. This generative and recursive model of HCI emphasises the importance of: (a) accurately monitoring the psychological state of the user (as discussed in the previous sections), and (b) equipping software with a repertoire of adaptive responses that covers the full range of possible outcomes within the human-computer dialogue over a period of sustained use. The latter point is particularly important for 'future-proofing' the physiological computing system as user and machine are locked into a co-evolutionary spiral of mutual adaptation (Fairclough, 2007).

Research into motivation for players of computer games has emphasised the importance of autonomy and competence (Ryan, Rigby, & Przybylski, 2006), i.e. choice of action, challenge and the opportunity to acquire new skills. This kind of finding begs the question of whether the introduction of a biocybernetic loop, which 'manages' the HCI according to preconceived meta-goals, represents a threat to the autonomy and competence of the user? Software designed to automatically help or manipulate task demand runs the risk of disempowerment by preventing excessive exposure to either success or failure. This problem was articulated by Picard & Klein (2002) who used the phrase 'computational soma' to describe affective computing software that effectively diffused and neutralised negative emotions. Feelings of frustration or anger serve as potent motivators within the context of a learning process; similarly, anxiety or fatigue are valuable psychological cues for the operator of a safety-critical system. It is important that the sensitivity of the biocybernetic loop is engineered to prevent over-corrective activation and interventions are made according to a conservative regime. In other words, the user should be allowed to experience a negative emotional state before the system responds. This is necessary for the system to demonstrate face validity, but not to constrain users' self-regulation of behaviour and mood to an excessive degree.

The biocybernetic loop encapsulates the values of the system and embodies a dynamic that promotes stable or unstable task performance. The dynamics of the control loop may be alternated for certain application to avoid the placement of excessive constraints on user behaviour.

3.4 Ethics and Privacy

A number of ethical issues are associated with the design and use of physiological computing systems. This technology is designed to tap private psychophysiological events and use these data as the operational fulcrum for a dynamic HCI. The ethical intention and values of the system designer are expressed by the meta-goals that control the biocybernetic loop (see previous section), but regardless of designers' good intentions, the design of any technology may be subverted to undesirable ends and physiological computing systems offer a number of possibilities for abuse (Reynolds & Picard, 2005b).

Invasion of privacy is one area of crucial concern for users of physiological computing systems. Ironically, a technology designed to promote symmetrical communication between user and system creates significant potential for asymmetry with respect to data protection, i.e. the system may not tell the user where his or her data are stored and who has access to these data. If data protection rights are honored by the physiological computing system, it follows that ownership of psychophysiological data should be retained formally and legally by the individual (Hancock & Szalma, 2003). One's own psychophysiological data are potentially very sensitive and access to other parties and outside agencies should be subject to formal consent from the user; certain categories of psychophysiological data may be used to detect medical conditions (e.g. cardiac arrhythmias, hypertension, epilepsy) of which the individual may not even be aware. The introduction of physiological computing should not provide a covert means of monitoring individuals for routine health problems without consent. In a similar vein, Picard & Klein (2002) argued that control of the monitoring function used by an affective computing system should always lie with the user. This is laudable but impractical for the user who wishes to benefit from physiological computing technology whilst enjoying private data collection. However, granting the user full control over the mechanics of the data collection process is an important means of reinforcing trust in the system.

Kelly (2006) proposed four criteria for information exchange between surveillance systems and users that are relevant here:

1. The user knows exactly what information is being collected, why it is being collected, where these data are stored and who has access to these data.
2. The user has provided explicit or implicit consent for data collection and can demonstrate full knowledge of data collection.
3. The user has access to these data, the user may edit these data or use these data himself or herself

4. Users receive some benefit for allowing the system to collect these data (e.g. recommendations, filtering).

This 'open source' relationship between user and technology is called reciprocal accountability (Brin, 1999). This relationship may be acceptable for users of physiological computing systems provided the apparent transparency of the process does not mask crucial inequalities, i.e. vague formulations of data rights by private companies or governments. The provision of written consent to specify this relationship should allay users' concerns and there is evidence (Reynolds & Picard, 2005a) to support this position.

A second threat to privacy concerns how psychophysiological data recorded in real-time may be expressed at the interface, i.e. feedback at the interface on user state may be perceived by colleagues or other persons when the computer is situated in a public space. The provision of explicit verbal messages or discrete text/symbolic messages in response to the detection of frustration or boredom are potentially embarrassing for the user in the presence of others. The fact that computer systems are used in public spaces constitutes a call for discretion on the part of the interface design, particularly with respect to the use of auditory feedback. It would also be essential to include a facility that enables users to disable those messages or modes of feedback that leave them susceptible to 'eavesdropping' by others.

Physiological computing systems are designed to 'manipulate' the state of the user in a benign direction via the positive meta-goals of the biocybernetic loop. But how do users feel about being manipulated by autonomous technology (Picard & Klein, 2002; Reynolds & Picard, 2005a)? The verb 'manipulate' is a loaded term in this context as people manipulate their psychological state routinely via psychoactive agents (e.g. caffeine, nicotine, alcohol), leisure activities (e.g. exercise, playing computer games) and aesthetic pastimes (e.g. listening to music, watching a TV show or movie) (Picard & Klein, 2002). The issue here is not the manipulation of psychological state per se but rather who retains control over the process of manipulation. When a person exercises or listens to music, they have full control over the duration or intensity of the experience, and may balk at the prospect of ceding any degree of control to autonomous technology. These concerns reinforce arguments that reciprocal accountability and granting the individual full control over the system are essential strategies to both reassure and protect the user. In addition, users need to understand how the system works so they are able understand the range of manipulations they may be subjected to, i.e. an analytic method for tuning trust in an automated system (Miller, 2005).

Physiological computing systems have the potential to be subverted to achieve undesirable outcomes such as invasion of privacy and tacit manipulation of the user. It is impossible to safeguard any new technology in this respect but provision of full transparency and reciprocal accountability drastically reduces the potential for abuse. It is important that the user of a physiological computing system remains in full control of the process of data collection (Picard & Klein, 2002) as this category of autonomous technology must be designed to empower the user at every opportunity (Hancock, 1996; Norman, 2007).

4. Summary

The concept of physiological computing allows computer technology to interface directly with the human nervous system. This innovation will allow users to provide direct input control to technology via specific changes in muscle tension and brain activity that are intentional. Data provided by wearable sensors can be used to drive biocybernetic adaptation and for ambulatory monitoring of physiological activity. In these cases, physiological changes are passively monitored and used as drivers of real-time system adaptation (biocybernetic adaptation) or to mark specific patterns that have consequences for health (ambulatory monitoring). The concept of biofeedback is fundamental to all categories of physiological computing as users may use these systems to promote increased self-regulation with respect to novel input devices (muscle interfaces or BCI), emotional control and stress management. Five different categories of physiological computing systems have been described (Muscle Interface, BCI, Biofeedback, Biocybernetic Adaptation, Ambulatory Monitoring) and there is significant overlap between each category. In addition, these physiological computing systems may be used to augment conventional input control in order to extend the communication bandwidth of the HCI.

The benefits of the physiological computing paradigm are counteracted by a number of potential risks, including systems that provide a mismatch with the behavioural state of the user or diminish user autonomy or represent a considerable threat to personal privacy. It is argued that the sensitivity of physiological computing system is determined by the diagnosticity of the psycho-physiological inference, i.e. the ability of the physiological data to consistently index target behaviour regardless of environmental factors or individual differences. It was also proposed that the biocybernetic control loop (the process by which physiological changes are translated into computer control) be carefully designed in order to promote design goals (e.g. safety and efficiency) without jeopardising the primacy of user control. The privacy of the individual is of paramount importance if physiological computing systems are to be acceptable to the public at large. A number of security issues were discussed with reference to controlling access to personal data and empowering the data protection rights of the individual.

References

Aarts, E. (2004). Ambient Intelligence: a multimedia perspective. IEEE Multimedia, 11(1), 12-19.

Ahn, H., Teeters, A., Wang, A., Breazeal, C., & Picard, R. W. (2007). Stoop to conquer: posture and affect interact to influence computer users' persistence. Paper presented at the Second International Conference on Affective Computing and Intelligent Interaction, Lisbon, Portugal.

Allison, B., Graimann, B., & Graser, A. (2007). Why use a BCI if you are healthy? Paper presented at the ACE Workshop - Brainplay'07: Brain-Computer Interfaces and Games, Salzburg.

Allison, B. Z., Wolpaw, E. W., & Wolpaw, J. R. (2007). Brain-computer interface systems: progress and prospects. Expert Review of Medical Devices, 4 (4), 463-474.

Baber, C., Haniff, D. J., & Woolley, S. I. (1999). Contrasting paradigms for the development of wearable computers. IBM Systems Journal, 38(4), 551-565.

Bartlett, M., Littlewort, G., Fasel, I., & Morvellan, J. R. (2003). Real time face detection and facial expression recognition: development and application to human-computer interaction. Paper presented at the Computer Vision and Pattern Recognition for Human-Computer Interaction, Vancouver, Canada.

Brin, D. (1999). The Transparent Society: Will Technology Force Us to Choose between Privacy and Freedom: Perseus Books.

Burleson, W., & Picard, R. W. (2004). Affective agents: sustaining motivation to learn through failure and a state of "stuck". Paper presented at the Workshop on Social and Emotional Intelligence in Learning Environments.

Cacioppo, J. T., Berntson, G. G., Malarkey, W., Kiecolt-Glaser, J. K., Sheridan, J. F., Poehlmann, K., et al. (1998). Autonomic, neuroendocrine and immune responses to psychological stress: the reactivity hypothesis. Annals of the New York Academy of Sciences, 840, 664-673.

Cacioppo, J. T., & Tassinary, L. G. (1990). Inferring psychological significance from physiological signals. American Psychologist, 45(1), 16-28.

Cacioppo, J. T., Tassinary, L. G., & Berntson, G. G. (2000a). Handbook of Psychophysiology: Cambridge University Press.

Cacioppo, J. T., Tassinary, L. G., & Berntson, G. G. (2000b). Psychophysiological Science. In J. T. Cacioppo, L. G. Tassinary & G. G. Berntson (Eds.), Handbook of Psychophysiology (pp. 3-26). Cambridge UK: Cambridge University Press.

Chin, C. A., Barreto, A., Cremades, J. G., & Adjouadi, M. (2008). Integrated electromyogram and eye-gaze tracking cursor control system for computer users with motor disabilities. Journal of Rehabilitation Research & Development, 45(1), 161-174.

Coan, J. A., & Allen, J. J. B. (2003). Frontal EEG asymmetry and the behavioural activation and inhibition systems. Psychophysiology, 40, 106-114.

Dekker, A., & Champion, E. (2007). Please biofeed the zombies: enhancing the gameplay and display of a horror game using biofeedback. Paper presented at the DiGRA.

Ebner-Priemer, U. W., & Trill, T. J. (2009). Ambulatory assessment: an innovative and promising approach for clinical psychology. European Psychologist, 14(2), 109-119.

Fairclough, S. H. (2007). Psychophysiological inference and physiological computer games. Paper presented at the ACE Workshop - Brainplay'07: Brain-Computer Interfaces and Games.

Fairclough, S. H. (2008). BCI and Physiological Computing: Similarities, Differences and Intuitive Control. Paper presented at the Workshop on BCI and Computer Games: CHI'08.

Fairclough, S. H. (2009). Fundamentals of Physiological Computing. Interacting With Computers, 21, 133-145.

Fairclough, S. H., & Venables, L. (2004). Psychophysiological candidates for biocybernetic control of adaptive automation. In D. de Waard, K. A. Brookhuis & C. M. Weikert (Eds.), Human Factors in Design (pp. 177-189). Maastricht: The Netherlands: Shaker.

Fairclough, S. H., Venables, L., & Tattersall, A. (2006). The use of autonomic measures for biocybernetic adaptation. Psychophysiology, 42(S1), S25.

Freeman, F. G., Mikulka, P. J., Scerbo, M. W., & Scott, L. (2004). An evaluation of an adaptive automation system using a cognitive vigilance task. Biological Psychology, 67, 283-297.

Gevins, A., Smith, M. E., Leong, H., McEvoy, L., Whitfield, S., Du, R., et al. (1998). Monitoring working memory load during computer-based tasks with EEG pattern recognition models. Human Factors, 40(1), 79-91.

Gilleade, K. M., & Dix, A. (2004). Using frustration in the design of adaptive videogame. Paper presented at the Advances in Computer Entertainment Technology.

Gilleade, K. M., Dix, A., & Allanson, J. (2005). Affective videogames and modes of affective gaming: assist me, challenge me, emote me. Paper presented at the Proceedings of DiGRA 2005.

Grauman, K., Betke, M., Gips, J., & Bradski, G. R. (2001). Communication via eye blinks - detection and duration analysis in real time. Paper presented at the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'01).

Grimes, D., Tan, D. S., Hudson, S. E., Shenoy, P., & Rao, R. P. N. (2008). Feasibility and pragmatics of classifying working memory load with an electroencelograph. Paper presented at the CHI 2008.

Guger, C., Edlinger, A. G., Harkam, W., Niedermayer, I., & Pfurtscheller, G. (2003). How many people are able to operate an EEG-based brain-computer interface (BCI)? IEEE Transactions on Neural Systems and Rehabilitation Engineering, 11(2), 145-147.

Hancock, P. A. (1996). Teleology for Technology. In R. Parasuraman & M. Mouloua (Eds.), Automation and Human Performance (pp. 461-497). Hillsdale, N. J.: Erlbaum.

Hancock, P. A., Pepe, A. A., & Murphy, L. L. (2005). Hedonomics: the power of positive and pleasurable ergonomics. Ergonomics In Design, 13(1), 8-14.

Hancock, P. A., & Szalma, J. L. (2003). The future of neuroergonomics. Theoretical Issues in Ergonomic Science, 44(1-2), 238-249.

Healey, J., & Picard, R. W. (1997). Digital processing of affective signals. Paper presented at the Proceedings of ICASSP, Seatle, WA.

Helander, M. G., & Tham, M. P. (2003). Hedonomics - affective human factors design. Ergonomics, 46(13/14), 1269-1272.

Hettinger, L. J., Branco, P., Encarnaco, L. M., & Bonato, P. (2003). Neuroadaptive technologies: applying neuroergonomics to the design of advanced interfaces. Theoretical Issues in Ergonomic Science, 4(1-2), 220-237.

Huang, C. N., Chen, C. H., & Chung, H. Y. (2006). Application of facial electromyography in computer mouse access for people with disabilities. Disability & Rehabilitation, 28(4), 231-237.

Kapoor, A., Burleson, W., & Picard, R. W. (2007). Automatic prediction of frustration. International Journal of Human-Computer Studies, 65, 724-736.

Karwowski, W. (2000). Symvatology: the science of artifact-human compatibility. Theoretical Issues in Ergonomic Science, 1(1), 76-91.

Kelly, K. (2006). The Technium Available from http://www.kk.org/thetechnium/archives/2006/02/symmetrical_and.php

Klein, G., Woods, D. D., Bradshaw, J. M., Hoffman, R. R., & Feltovich, P. J. (2004). Ten challenges for making automation a "team player" in joint human-agent activity. IEEE Intelligent Systems, 19(6), 91-95.

Kosmack Vaara, E., Hook, K., & Tholander, J. (2009). Mirror bodily experiences over time. Paper presented at the CHI Boston, MA.

Kulic, D., & Croft, E. (2005). Anxiety detection during human-robot interaction. Paper presented at the Conference on Intelligent Robots and Systems, Edmonton, Canada.

Kulic, D., & Croft, E. (2006). Estimating robot induced affective state using Hidden Markov Models. Paper presented at the IEEE International Symposium on Robot and Human Interactive Communication.

Lisetti, C. L., & Nasoz, F. (2004). Using noninvasive wearable computers to recognize human emotions from physiological signals. EURASIP Journal on Applied Signal Processing, 11, 1672-1687.

Lisetti, C. L., Nasoz, F., LeRouge, C., Ozyer, O., & Alvarez, K. (2003). Developing multimodal intelligent affective interfaces for tele-home health care. International Journal of Human-Computer Studies, 59, 245-255.

Liu, C., Rani, P., & Sarkar, N. (2005). An empirical study of machine learning techniques for affect recognition in human-robot interaction. Paper presented at the IEEE Conference on Intelligent Robots and Systems.

Mandryk, R. L., & Atkins, M. S. (2007). A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. International Journal of Human-Computer Studies, 65, 329-347.

Mandryk, R. L., Inkpen, K. M., & Calvert, T. W. (2006). Using psychophysiological techniques to measure user experience with entertainment technologies. Behaviour and Information Technology, 25 (2), 141-158.

McFetridge-Durdle, J. A., Routledge, F. S., Parry, M. J. E., Dean, C. R. T., & Tucker, B. (2008). Ambulatory impedance cardiography in hypertension: a validation study. European Journal of Cardiovascular Nursing, 7, 204-213.

Merrill, D., & Maes, P. (2007). Augmenting looking, pointing and reaching gestures to enhance the searching and browsing of physical objects. Paper presented at the 5th International Conference on Pervasive Computing (Pervasive'07), Toronto, Ontario, Canada.

Microsoft Project Natal http://www.xbox.com/en-US/live/projectnatal/

Milenkovic, A., Otto, C., & Jovanov, E. (2006). Wireless sensor networks for personal health monitoring: issues and an implementation. Computer Communications, 29, 2521-2533.

Miller, C. A. (2005, July 22nd-27th). Trust in adaptive automation: the role of etiquette in tuning trust via analogic and affective methods. Paper presented at the First International Conference on Augmented Cognition, Las Vegas, NV.

Morris, M., & Guilak, F. (2009). Mobile Heart Health: Project Highlight. IEEE Pervasive Computing, 8(2), 57-61.

Morris, M. E. (2007). Technologies for heart and mind: new directions in embedded assessment. Intel Technology Journal, 11(1), 67-74.

Murata, A. (2006). Eye gaze input versus mouse: cursor control as a function of age. International Journal of Human-Computer Interaction, 21(1), 1-14.

Naik, G. R., Kumar, D. K., & Arjunan, S. P. (2008). Multi modal gesture identification for HCI using surface EMG. Paper presented at the 12th International Conference on Entertainment and Media in the Ubiquitous Era, Tampere, Finland.

Norman, D. A. (2007). The Design of Future Things. New York: Basic Books.

O'Donnell, R. D., & Eggemeier, F. T. (1986). Workload assessment methodology. In K. Boff, L. Kaufman & J. Thomas (Eds.), Handbook of Human Perception and Performance (Vol. 2, pp. 42.41-42.49). New York: Wiley.

Picard, R. W. (1997). Affective Computing. Cambridge, Mass.: MIT Press.

Picard, R. W., & Healey, J. (1997). Affective wearables. Personal Technologies, 1, 231-240.

Picard, R. W., & Klein, J. (2002). Computers that recognise and respond to user emotion: theoretical and practical implications. Interacting With Computers, 14, 141-169.

Picard, R. W., Vyzas, E., & Healey, J. (2001). Towards machine emotional intelligence: analysis of affective physiological state. IEEE Transactions on Pattern Analysis and Machine Intelligence, 23(10), 1175-1191.

Pope, A. T., Bogart, E. H., & Bartolome, D. S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. Biological Psychology, 40, 187-195.

Prinzel, L. J., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2000). A closed-loop system for examining psychophysiological measures for adaptive task allocation. The International Journal of Aviation Psychology, 10(4), 393-410.

Prinzel, L. J., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2003). Effects of a psychophysiological system for adaptive automation on performance, workload, and the event-related potential P300 component. Human Factors, 45(4), 601-613.

Prinzel, L. J., Parasuraman, R., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2003). Three experiments examining the use of electroencephalogram, event-related potentials, and heart-rate variability for real-time human-centred adaptive automation design (No. NASA/TP-2003-212442): NASA.

Prinzel, L. J., Pope, A. T., & Freeman, F. G. (2002). Physiological self-regulation and adaptive automation. The International Journal of Aviation Psychology, 12(2), 179-196.

Rani, P., & Sarkar, N. (2007). Operator engagement detection for robot behaviour adaptation. International Journal of Advanced Robotic Systems, 4(1), 1-12.

Rani, P., Sarkar, N., & Liu, C. (2005). Maintaining optimal challenge in computer games through real-time physiological feedback. Paper presented at the 11th Human-Computer Interaction International, Las Vegas, USA.

Rani, P., Sims, J., Brackin, R., & Sarkar, N. (2002). Online stress detection using psychophysiological signal for implicit human-robot cooperation. Robotica, 20(6), 673-686.

Rashidi, P., & Cook, D. J. (in press). Keeping the resident in the loop: adapting the smart home to the user. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans.

Reynolds, C., & Picard, R. W. (2005a). Affective sensors, privacy and ethical contracts. Paper presented at the CHI'2005, Vienna, Austria.

Reynolds, C., & Picard, R. W. (2005b). Evaluation of affective computing systems from a dimensional metaethical position. Paper presented at the First Augmented Cognition Conference, Las Vegas, Nevada.

Ryan, R. M., Rigby, C. S., & Przybylski, A. (2006). The motivational pull of video games: a self-determination approach. Motivation and Emotion, 30, 347-363.

Saponas, T. S., Tan, D. S., Morris, D., & Balakrishnan, R. (2008). Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces. Paper presented at the CHI.

Scerbo, M. W., Freeman, F. G., & Mikulka, P. J. (2003). A brain-based system for adaptive automation. Theoretical Issues in Ergonomic Science, 4(1-2), 200-219.

Scheirer, J., Fernandez, R., Klein, J., & Picard, R. W. (2002). Frustrating the user on purpose: a step toward building an affective computer. Interacting With Computers, 14, 93-188.

Schwartz, M. S., & Andrasik, F. (2003). Biofeedback: a practioners guide: Guildford Press.
Tecce, J. J., Gips, J., Olivieri, C. P., Pok, L. J., & Consiglio, M. R. (1998). Eye movement control of computer functions. International Journal of Psychophysiology, 29, 319-325.
Teller, A. (2004). A platform for wearable physiological computing. Interacting With Computers, 16, 917-937.
Wachsmuth, S., Wrede, S., & Hanheide, M. (2007). Coordinating interactive vision behaviours for cognitive assistance. Computer Vision and Image Understanding, 108, 135-149.
Wickens, C. D. (2002). Multiple resources and performance prediction. Theoretical Issues in Ergonomic Science, 3, 150-177.
Wilson, G. F., & Russell, C. A. (2003). Operator functional state classification using multiple psychophysiological features in an air traffic control task. Human Factors, 45(3), 381-389.
Wilson, G. F., & Russell, C. A. (2007). Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding. Human Factors, 49(6), 1005-1018.
Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., McFarland, D. J., Peckham, P. H., Schalk, G., et al. (2000). Brain-computer interface technology: a review of the first international meeting. IEEE Transactions on Rehabilitation Engineering, 8, 164-173.
Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain-computer interfaces for communication and control. Clinical Neurophysiology, 113, 767-791.
Wolpaw, J. R., & McFarland, D. J. (2004). Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. Proceedings of National Academy of Science USA, 101, 17849-17854.
Yannakakis, G. N., Hallam, J., & Hautop Lund, H. (2007). Entertainment capture through heart rate activity on physical interactive playgrounds. User Modeling and User-Adapted Interaction, 18, 207-243.
Zander, T. O., & Jatzev, S. (2009). Detecting affective covert user states with passive Brain-Computer Interfaces. Paper presented at the Affective Computing and Intelligent Interaction (ACII'09).