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Enhancing video game performance through an individualized biocybernetic system

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Enhancing video game performance through an individualized biocybernetic system

by

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ABSTRACT

Biocybernetic systems are physiological software systems that explicitly utilize physiological signals to control or adapt software functionality (Pope et al., 1995.) These systems have tremendous potential for innovation in human computer interaction by using physiological signals to infer a user's emotional and mental states (Allanson & Fairclough, 2004; Fairclough, 2008). Nevertheless, development of these systems has been ultimately hindered by two fundamental challenges. First, these systems make generalizations about physiological indicators of cognitive states across populations when, in fact, relationships between physiological responses and cognitive states are specific to each individual (Andreassi, 2006). Second, they often employ largely inconsistent retrospective techniques to subjectively infer user's mental state (Fairclough, 2008).

An individualized biocybernetic system was developed to address the fundamental challenges of biocybernetic research. This system was used to adapt video game difficulty through real-time classifications of physiological responses to subjective appraisals. A study was conducted to determine the system's ability to improve player's performance. The results provide evidence of significant task performance increase and higher attained task difficulty when players interacted with the game using the system than without. This work offers researchers with an alternative method for software adaptation by conforming to the individual characteristics of each user.

DEFINITIONS

The following terms were defined for use in this study:

Affect Module: A mental model defining the relationships between different cognitive or emotional states.

Biocybernetic systems: A term coined by Alan Pope to describe systems which explicitly utilize physiological signals to control or adapt software functionality (Pope et al., 1995).

Individual response specificity: The individualized characteristics of physiological responses to stimuli (Andreassi, 2006).

Physiological computing: The use of physiological signals for computer input (Allanson & Fairclough, 2004; Fairclough, 2008). It extends upon psychophysiological research by directly interfacing human physiology and computer technology to create expressive communication between humans and computers (Allanson & Fairclough, 2004).

Psychophysiology: "…the study of relations between psychological manipulations and resulting physiological responses, measured in the living organism, to promote understanding of the relations between mental and bodily processes" (Andreassi, 2006, p. 2).

Psychophysiological classifications: Categorization of specific psychophysiological relationships between particular physiological signals and specific cognitive states.

Psychophysiological validity: Concerned with the correct interpretations of psychological states from physiological signals (Andreassi, 2006).

CHAPTER 1. INTRODUCTION

Background

Physiological computing is the domain of computer systems that use physiological signals for computer input (Allanson & Fairclough, 2004; Fairclough, 2008). Biocybernetic systems are physiological software systems that explicitly utilize physiological signals to control or adapt software functionality (Pope et al., 1995.) These systems have tremendous potential for innovation in human computer interaction by using physiological signals to infer a user's emotional and mental states (Allanson & Fairclough, 2004; Fairclough, 2008). Nevertheless, development of these systems has been ultimately hindered by two fundamental challenges. First, these systems make generalizations about psychophysiological patterns across populations when, in fact, relationships between physiological responses and cognitive states are specific to each individual (Andreassi, 2006). Second, they often employ largely inaccurate retrospective techniques to infer user's mental state (Fairclough, 2008).

An alternative approach can be developed to address these problems. This individualized approach should make no presumptions on how an individual's physiology translates to mental state; rather, it should develop knowledge about each individual while they engage in the task at hand. A system using this approach would adjust task features specifically to each individual without making generalized assumptions about a person's physiology and without relying on retrospective evaluations. Accomplishing this requires a system to perform two activities concurrently while individuals interact with the system. First, establish psychophysiological classifications, and second, adapt task features.

Performing these activities in real-time requires alternative techniques to that of generalized systems which collect subjective input and establish psychophysiological relationships after a task has been completed.

Problems of the Study

There are three problems examined in this study. (1) Subjective appraisals must be gathered at time of experience in order to circumvent the faults of retrospective evaluations. However subjective appraisals are difficult to gather in real time (Ikehara & Crosby, 2005); (2) The inherent variability between different individuals' physiologies requires specific psychophysiological classifications for each individual, task and situation. Psychophysiological classifications are categorizations of physiological patterns established for particular cognitive states. (3) Appropriate task parameters must be selected and appropriately adapted, within an application, to allow for the possibility of enhancing a user's performance,

Need and Rationale for the Study

There are three reasons that this current study was conducted: (1) Psychophysiological patterns are different between all individuals. True, personalized adaptation through physiological computing is not possible using current, generalized methods. (2) Different situations can affect how well physiological data are collected and how users interact with a software system. Establishing psychophysiological classifications while users interact with the system would accommodate these possible variances by building classifications specifically for each situation. (3) The current pre-requisites for research and development of biocybernetic systems are quite high. Aside from requiring

specific knowledge of signal processing, software development, machine learning, psychology and physiology, there are few software implementations available to persuade new researchers to experiment with biocybernetic systems. This is unfortunate as both physiological computing and biocybernetic systems have potential to innovate many domains of software applications. This research can serve as an architecture / framework prototype for developing a more generalized set of software libraries to help lower the learning curve of biocybernetic development and research.

Scope

The study was limited to an initial proof-of-concept of individualized biocybernetic systems. Evaluations presented here consider performance only against a control group and not against generalized physiological computing systems. Additionally, this study only considers a small set of physiological signals, one type of classification method (artificial neural network), and task adaptations specific to a single video game application. However, the software and methodologies developed here can be applicable to other physiological signals, classification methods, and system adaptations.

CHAPTER 2. LITERATURE REVIEW

Physiological computing is the domain of computer systems that use physiological signals for computer input (Allanson & Fairclough, 2004; Fairclough, 2008). Biocybernetic systems are physiological software systems that explicitly utilize physiological signals to control or adapt software functionality (Pope et al., 1995.) These systems have tremendous potential for innovation in human computer interaction by using physiological signals to infer a user's emotional and mental states (Allanson & Fairclough, 2004; Fairclough, 2008). Nevertheless, development of these systems has been ultimately hindered by two fundamental challenges. First, these systems make generalizations about psychophysiological patterns across populations when, in fact, relationships between physiological responses and cognitive states are specific to each individual (Andreassi, 2006). Second, they often employ largely inaccurate retrospective techniques to infer user's mental state (Fairclough, 2008).

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task has been completed. Before elaborating on the design of individualized systems, an overview is provided on the different phases of physiological computing leading up to biocybernetic systems. Also provided is an elaboration on current challenges.

<div align="center">**Physiological Computing Research Hierarchy**</div>

Physiological computing has been developed from studies relating physiological changes to mental states. The research has progressed from experiments establishing patterns between various physiological signals and mental states, through the use of software programs to learn these patterns and finally, to systems utilizing these algorithms to adapt software appropriately to user's mental state.

Psychophysiology

Psychophysiology is defined as "…the study of relations between psychological manipulations and resulting physiological responses, measured in the living organism, to promote understanding of the relations between mental and bodily processes" (Andreassi, 2006, p. 2). The human body is a chemical, electrical, mechanical, thermal and magnetic system with a multitude of signals, all with possible psychophysiological ramifications (Allanson & Fairclough, 2004). The concept of psychophysiology stems from the physiological responses to psychological manipulations on three areas of the human nervous system—the central nervous system (CNS), the somatic nervous system (SNS), and the autonomic nervous system (ANS)—which then map to the cortical, somatic and autonomic systems, respectively (Andreassi, 2006). The CNS includes the brain and spinal cord; the SNS controls muscles; and the ANS controls and coordinates the major glands and organs.

A plethora of research studies have been conducted to understand the nature of a wide variety of physiological signals and their relationships to various mental states. Typical physiological signals investigating the ANS include: electrodermal activity (EDA) (Chanel, Rebetez, BÈtrancourt, & Pun, 2008; Mandryk & Atkins, 2007; Rani, Sarkar, & Liu, 2005; Yannakakis & Hallam, 2008); blood pressure (Chanel et al., 2008); heart hate (HR) (Chanel et al., 2008; Mandryk & Atkins, 2007; Yannakakis & Hallam, 2008), heart rate variability (HRV) (Mandryk & Atkins, 2007; Rani et al., 2005; Rowe, Sibert, & Irwin, 1998); impedance cardiography (ICG) (Rani et al., 2005), blood volume (Rani et al., 2005; Yannakakis & Hallam, 2008), Respiration (Chanel et al., 2008); and temperature (Chanel et al., 2008; Rani et al., 2005). Investigations in the SNS include electromyography (EMG) (Mandryk & Atkins, 2007; Rani et al., 2005), and extraocular muscles (EOM) (Ikehara & Crosby, 2005). Finally research into the CNS includes electroencephalography (EEG) (Pope, Bogart, & Bartolome, 1995) and event related potentials (ERP) (Andreassi, 2006).

In basic psychophysiological experiments, subjects are introduced to psychological manipulations while specific physiological signals are monitored for significant changes (Andreassi, 2006). Typically, mental states are evaluated through retrospective investigations such as interviews or surveys. The results are often connected to affect models to describe how changes in physiological responses correspond to changing mental states.

These affect models are as varied as much as the different physiological signals that have been investigated. However, these models are mainly derivatives of the initial work on stress coping (Lazarus & Folkman, 1984) and positive psychology's Flow model (Csikszentmilhalyi, 1975). Both works develop models for describing the effects of different mental loads on working memory. Examples of these studies include: task challenge by

subject skill level, (Chanel et al., 2008; Csikszentmihalyi & Csikzentmihaly, 1990; Rani et al., 2005); valence by arousal (Lang, 1995; Mandryk, Atkins, & Inkpen, 2006); regulation of arousal through stress quality (Blascovich & Tomaka, 1996); challenge / curiosity / fantasy (Yannakakis & Hallam, 2007); non-specific models of fun (Yannakakis & Hallam, 2008; Mandryk & Inkpen, 2004); and arousal by pleasure (Mandryk & Atkins, 2007; Russell, Weiss, & Mendelsohn, 1989). Unfortunately, no standardized affect model is used in physiological computing research.

Using an affect model, the physiological signals are statistically mapped to the mental states. Basic psychophysiological research employs a variety of correlational and regression techniques. However, machine learning techniques are predominate in physiological computing research. The basic procedure for evaluating an effective technique is a two stage process: First, a psychophysiological experiment is conducted to gather both physiological signal data and mental states. If significant patterns are found, a learning algorithm is selected whose properties appropriately fit the characteristics of the discovered pattern. This algorithm is trained on the initial experiment's data. In the second stage, a follow-up experiment is conducted similar to the initial experiment.   Upon completion, the subject's mental states are both recorded retrospectively through subjective evaluations and predicted with the training algorithm. The results of the retrospective evaluations and algorithm's predictions are then compared to evaluate the success of the trained algorithm. Various predictive techniques used to classify physiology, including fuzzy logic (Graesser, 1999; Mandryk, 2007); neural networks (Petrushin, 2000; Pope et al., 1995; Yannakakis & Hallam, 2008); k-nearest neighbors algorithm (Petrushin, 2000; Scherer, 1993); linear and nonlinear regression analysis (Moriyama & Ozawa, 2001; Rani et al., 2005); discriminate function

analysis (Ark, Dryer, & Lu, 1999); combinations of sequential floating forward search and fisher projection methods (Vyzas & Picard,1998); Bayesian classification (Qi &Picard,2002); naive bayes (Sebe, Lew, Cohen, Garg, & Huang, 2002); hidden Markov models (Cohen, Garg, & Huang, 2000); and support vector machines (Chanel et al., 2008).

Physiological Computing

Physiological computing extends upon psychophysiological research by directly interfacing human physiology and computer technology to create expressive communication between humans and computers (Allanson & Fairclough, 2004). There are many attributes of human physiology that are beneficial for computer input. Physiological signals provide continuous input from the user without explicit user interaction. The signals can be measured systematically regardless of task, and can be collected in real-time without affecting user's performance (Ikehara & Crosby, 2005). When combined with the results of psychophysiological research, the attributes of physiological signals allow for physiological computing systems to continually communicate the user's mental state to a computer. This is highly valuable in situations in which full attention to a crucial, but perhaps, tedious task is essential (Girouard, 2009; Pope et al., 1995). For example, boredom, inattention, and stress have large impacts on task performance and are mental states sought after in physiological computing research.

The procedure for physiological computing research is similar to that of psychophysiological research and is also evaluated by retrospective appraisals of mental states. However, a key difference between them is that physiological computing research

tasks participants with interacting with software, where in psychophysiological research participants are tasked with psychological tests.

There are three main uses for physiological computing systems. 1) evaluation of software. 2) software adaptation, and 3) biofeedback therapy. However therapeutic biofeedback systems are not relevant in this discussion.

Evaluation of Software

Physiological computing systems have been used for a variety of evaluations such as software effectiveness (Chanel et al., 2008; Mandryk et al., 2006; Yannakakis & Hallam, 2008), improved artificial intelligence (Yannakakis & Hallam, 2007, 2008), computer-based collaboration (Mandryk & Inkpen, 2004), user engagement (Chanel et al., 2008; Pope et al., 1995; Rani et al., 2005), and intelligent tutoring systems (Graesser, Wiemer-Hastings, Wiemer-Hastings, & Kreuz, 1999; Karamouzis & Vrettos, 2007). Software evaluations that incorporate physiological systems have many benefits over other procedures. Most notably, physiological data are covert and abstract of the subject's conscious evaluation, allowing for more objective evaluations (Ikehara & Crosby, 2005). This is important as the differences between subjective and objective reports of software usability are significant (Wilson & Sasse, 2000). Other benefits of objective assessments include less susceptibility to effects of reappraisal, discounting, and self-representation biases (Chalabaev, Major, Cury, & Sarrazin, 2009; Chanel et al., 2008; Mandryk & Inkpen, 2004).

Software Adaptation

The second use for physiological computing is software adaptation or biocybernetic adaptation. The term biocybernetic was coined by Alan Pope to describe systems which explicitly utilize physiological signals to control or adapt software functionality (Pope et al., 1995). For example, if a user's physiological index of negative stress continues to increase, an adaptive controller can assume the user is stressed and proceed to automate system tasks. In theory, the reduction of a user's responsibility should eventually cause a reduction in his or her stress level to a normal level where system tasks can then return to the user's control. This feedback control loop between human and computer is at the heart of biocybernetic adaptation. Benefits of these systems include improved task performance, increased task engagement when used for sustained task performance periods (Freeman, Mikulka, Scerbo, Prinzel, & Clouatre, 2000), and reduction of subjectively assessed mental workload (Allanson & Fairclough, 2004).

Software adaptation from physiological signals is researched across multiple disciplines; no single term is used to encompass its entirety. Three terms have emerged to describe most of the current research. Along with the term biocybernetic systems, adaptive automation and affective adaptation are used to describe adaptation that can use physiological signals with slight differences. Automated adaptation is strictly interested in automating tasks to control the user's cognitive memory load (Freeman, Mikulka, Prinzel, & Scerbo, 1999). These systems can use physiological indicators as well as behavioral indicators for assessing the user's mental state. Affective adaptation systems (Picard, 2000), a sub-set of affective computing, strictly focuses on adapting software to emotional states of

users. These systems, like automated adaptation, use either behavioral or physiological indicators.

Challenges of Current Research

There are multiple challenges with current biocybernetic systems. A comprehensive discussion of these can be found in recent reviews of physiological computing (Allanson & Fairclough, 2004; Fairclough, 2009). However, two main themes emerge from the review: 1) the lack of control on validating psychophysiology, and 2) the challenge of objectively evaluating mental state.

Psychophysiological Validity

Andreassi (2006) noted that Psychophysiological validity is concerned with the correct interpretations of psychological states from physiological signalsPhysiological signals gathered from bodily functions have unique characteristics that are specific to each individual and situational context. These situational and individualized responses stem from the fact that most physiological signals are influenced by two or more underlying nervous systems. Therefore, it is troublesome for research to develop general models of physiological behavior.

Response Specificity

Individual response specificity is the individualized characterization of physiological responses to stimuli (Andreassi, 2006). Small changes in physical makeup (e.g., height, stress level, family history, etc.) have implications on the characteristics of an individual's physiological responses. For example, under everyday stress, patients with chronic anxiety

disorders tend to react with less physiological response than patients without chronic anxiety. However, they overreact, both subjectively and physiologically, to stimuli that are anxiety-provoking (Hoehn-Saric & McLeod, 2000). Due to this specificity, individual characteristics can alter the relationship between physiological signals and mental states. One individual's physiological relationship to mental states cannot be assumed to be relevant to that of other individuals.

To compound the issue, an individual's pattern of physiological responses may be similar only within a given situation, and that pattern may be different if the situation is different. Physiological responses cannot be assumed to be consistent across varying tasks or if the task is approached with a different state of mind. For example, a change of focus can alter one's physiological response to a task. During an experiment visualizing phobias, speech-anxious participants exhibited significantly decreased heart rate when asked to worry about how they would react to a phobic situation compared to participants who were engaged in relaxing thoughts prior to the task (Borkovec & Hu, 1990; Hoehn-Saric & McLeod, 2000). Thus, the sequence of mental states affects physiological responses. Conversely, numerous studies have been conducted producing different physiological patterns for similar emotions.

There is also the effect of directional fractionation wherein one physiological system might exhibit an increase in activation while others may show a decrease. An example of this is when an individual notices an item is missing, muscle tension and skin conductance might increase but heart rate may decrease (Andreassi, 2006). These effects add to the lack of extendibility of generalized psychophysiological patterns across physiological signals.

In summary, physiology is specific to the individual, the task, and the conditions when performing a task. Any generalization across a population will be fundamentally

restricted to at a least one of three areas. Only two options have been evaluated in the past: (a) create a psychophysiological pattern that is restricted to one or all three areas of specificity, and in doing so, ultimately restrict the pattern's applicability; or (b) generalize over the areas of specificity and reduce the pattern's ability to predict individual's mental states. However, a third option does exist. Psychophysiological patterns could be established as users interact with the system. Doing so will conform to all levels of specificity; individual, task, and context of operation.

Objective Appraisals of Mental State

There is considerable debate on whether subjective reporting corresponds to actual experience (Mandryk & Inkpen, 2004; Marshall & Rossman, 2006; Pagulayan, Keeker, Wixon, Romero, & Fuller, 2002; Wilson & Sasse, 2000). There is also a long research history of disassociation between subjective and objective measures (Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993). In one example that evaluates subjective appraisals of physiological states, patients with chronic anxiety disorders exhibit increased muscle tension but not autonomic arousal when at rest. This is contrary to their self-reports (Hoehn-Saric & McLeod, 2000). This inconsistency between self-reporting and physiological recordings could be explained by a variety of factors such as alterations of body sensations through psychological factors, mental expectations, or attention to bodily states that can lead to perceptual distortions (Hoehn-Saric & McLeod, 2000). Additionally, when anxiety disorder patients are asked to rate themselves on severity of symptoms, they report increased heart rate, sweatiness, and muscle tension upon performing a stressful task. However, they also show a blunted physiological reaction to laboratory stressors. Thus, their subjective

perception of bodily states is not congruent with their physical state (Hoehn-Saric & McLeod, 2000).

The detriments of self-reporting are not limited to subjective perceptions of physiology. There is a large discrepancy between subjective appraisals close to experience time and appraisals after a time delay on a variety of cognitive states (Fredrickson & Kahneman, 1993; Kahneman, 2000; Schwarz, 2000). Most notable is research on the discrepancy of immediate and retrospective appraisals of pain. Retrospective appraisals of pain are significantly different than the appraisals taken in realtime and tend to be significantly correlated to the last pain rating given (Kahneman et al., 1993; Kahneman, Wakker, & Sarin, May 1997; Redelmeier & Kahneman, 1996). Two retrospective evaluation heuristics have been established from this research: the peak-end rule and duration neglect. The peak-end rule indicates subjective appraisals tend to be heavily influenced by the ending state of an experience and has shown to account for between 86% and 98% of the variance of retrospective pain ratings (Kahneman, 2000). Duration neglect is the decrease in memory clarity of events over time. It also has a large effect on retrospective evaluations (Kahneman, 2000; Redelmeier & Kahneman, 1996). Both duration neglect and the peak-end rule are not surprising given the limitations of memory capacity (Kahneman et al., 1997).

Dual-process models of cognition are psychological models that describe human behavior resulting from interplay between controlled and automatic processing. These models indicate that there are limited amounts of resources available for attention and that different cognitive processes must compete for resources (Barrett, Tugade, & Engle, 2004). Within an experiment, both the cognitive processing for the primary experiment task and the subjective evaluation processing must compete against one another. As task engagement can

be considered as the level of cognitive resources directed toward a task, higher engagement on the primary experiment task would allow allocating less resources for reflection or self-assessment. This is in tune with the concept of Flow, where heightened involvement in activities have been correlated with subjective time loss (Csikszentmihalyi & Csikzentmihaly, 1990; Sackett, Meyvis, & Sackett, 2010) and research indicating subjective appraisals perform poorly at assessing subject's behavior (Mandryk & Inkpen, 2004). The limited cognitive resources for primary task engagement explicitly reduce the viability of subjective appraisal for evaluation of mental states. Along with duration neglect and peak-end rule, this adds a doubt into the validity of any evaluation of mental states evaluated using retrospective assessment.

Alternative Approach

As the review of literature has indicated, creating an individualized system must tread a fine line between the limitations of subjective appraisals and the complexities of psychophysiology. The individualized adaptation system gathers subjective data in real time using incremental subjective interpretations rather than retrospective analysis. Doing so should reduce or remove both the detrimental effects caused by physiological response specificity and retrospective evaluations. However, care must be taken as real-time subjective evaluation is difficult (Ikehara & Crosby, 2005).

Because subjective appraisals are gathered as users operate the system, the relationship of subjective appraisals to physiology will be initially weak but should grow stronger overtime. The value of the individualized adaptation system should then be greater

than generalized systems if the performance loss during initial use is replaced by later performance gains that are greater than that of the generalized systems.

In order to develop such an individualized system several unknowns must be investigated. First, it is still unknown whether real-time subjective appraisal can appropriately capture mental state. Second, can a software program learn the physiological patterns of mental states gathered from real-time subjective appraisals? Finally, can adaptations performed through this system improve task performance over systems without adaptation?

Research Questions

Three research questions guided this study:

1. Can real-time subjective appraisal appropriately capture mental state?

2. Can psychophysiological classifications be established in real time using subjective appraisal gathered at time of experience?

3. Can individual's task performance be improved through task adaptations controlled by real-time psychophysiological classifications?

CHAPTER 3. METHODOLOGY

The purpose of the study is to develop an individualized biocybernetic system for facilitating real-time task adaptation using psychophysiological patterns that are established from subjective appraisals taken at time of experience.   Two systems were created for this study: 1) A video game application to be adapted. 2) A set of software libraries implementing an individualized biocybernetic system.

Development of Video Game

An interactive video game was developed to test the viability of an individualized biocybernetic system to enhance user performance. A video game application was chosen for testing as it has multiple attributes that are beneficial for investigating individualized adaptation systems. Video games can be highly interactive, allowing for constant user interaction, as well as provide continuous challenge. Both of these attributes are advantageous for providing rapid subjective assessments and adaptation of difficulty. With a video game, it is possible to collect a large amount of subjective inputs within a short time frame. This high input frequency enables each subjective input to be mapped against a relatively small set of physiological data, thus, increasing the probability of stronger relationships between the physiological signals and subjective inputs.

The game: The game developed was similar to the popular top-down shooter series "Geometry Wars." This type of game is highly interactive, requires constant player feedback and typically has constant, increasing difficulty. Top down shooters typically employ a two-joystick control scheme. A similar control scheme was implemented for the game—one joystick for movement direction; the other, for firing direction (Figure 1). Additional

controls were implemented for navigating game menus and providing subjective appraisals of game difficulty.

Game difficulty was adjusted by increasing the amount, frequency, and type of enemy's introduced to the game. Three types of enemies were used which vary in the amount of effort required to destroy them. These enemy ships spawned in random locations within the game. Table 1 illustrates the player's ship and attributes of the three types of enemies used.
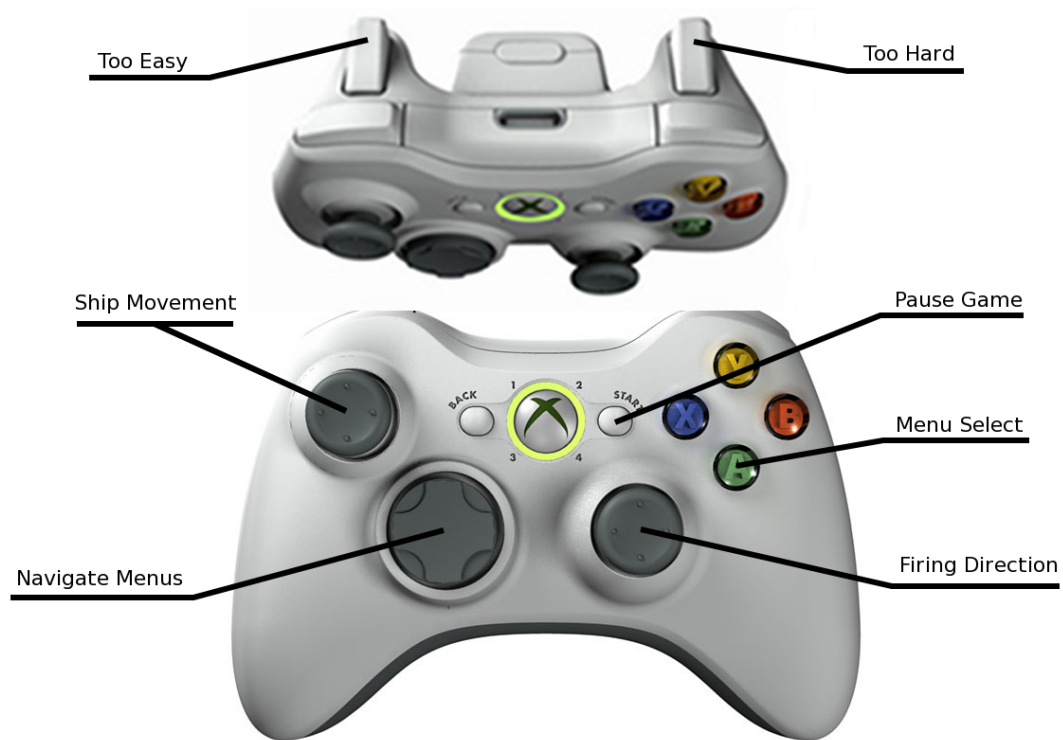
Figure 1. Game controls

Table 1 Player and Enemy Ships

Ship type	Description	Strength
	Ship controlled by the player can move in both x and y axis.	1 hit
	Easiest enemy ship to kill and moves linearly across the screen in the direction of the player's ship location.	1 hit
	Second easiest enemy ship to kill and moves across the screen in a wave pattern in the direction of the player's ship location.	5 hits
	Hardest enemy ship to kill. This ship follows the player's ship until it is destroyed.	10 hits

The game difficulty ranged from 0 to 100, where a difficulty of 0 had no enemies and a difficulty of 100 introduced 10 new enemies every 0.25 seconds. Players were awarded points for every enemy ship they destroyed. The amount of points awarded for each ship kill increased linearly based on the amount of enemies destroyed without a player death. The objective of the game was to score as many points are possible while staying alive.

Figures 2 and 3 illustrate games of high and low difficulties, respectively.

To facilitate subjective assessment of difficulty, players could have indicated desire to change the difficulty level during the game via a quick press of two buttons on the controller—the left trigger for decreasing the difficulty, the right trigger for increasing the difficulty. This appraisal of difficulty was used to classify the player's physiology for eventual automated adaptation. The Boolean scheme for changing difficulty was chosen in order to limit the effort required for players to enter information. Dual mode cognitive models indicate that limited resources are available for active cognitive processing (Barrett et al., 2004). As such, complex subjective appraisals have an increased risk of being ignored or becoming too distracting—interfering with the primary task. A limited input strategy should have provided the best possible mechanism for allowing real-time subjective appraisal. Players could adjust the difficulty at a frequency of 5 times a second.

Two changes to the gameplay were made from preliminary tests. First, an area bomb destroying nearby enemies was added when the decrease difficulty button was selected (Figure 4).
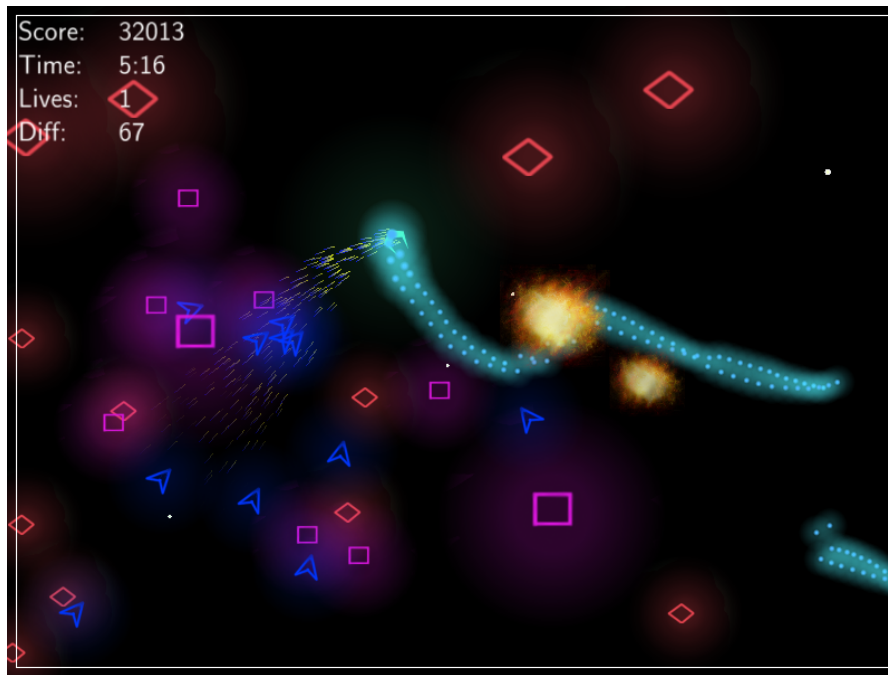
Figure 2. Game with high difficulty
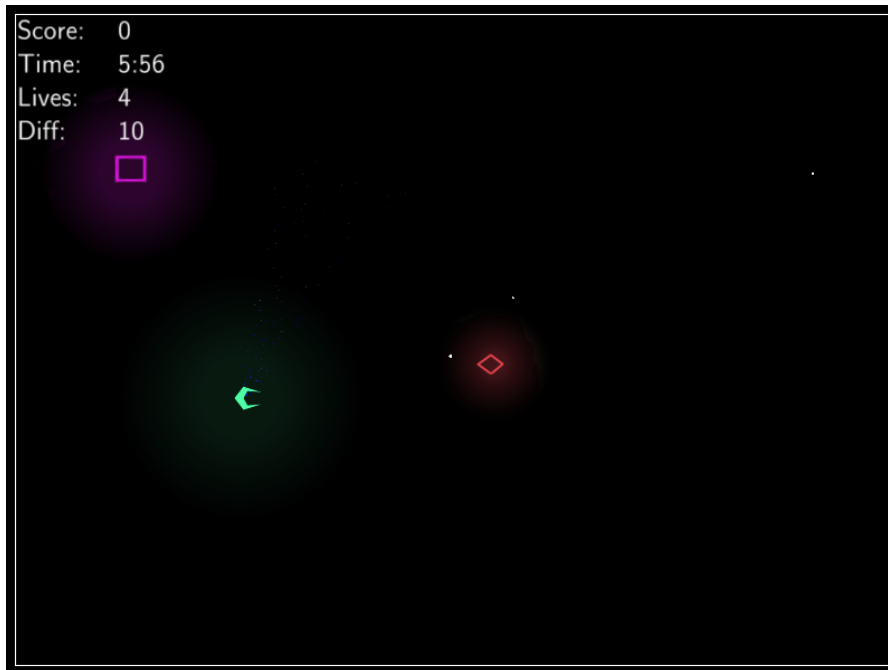
Figure 3. Game with low difficulty
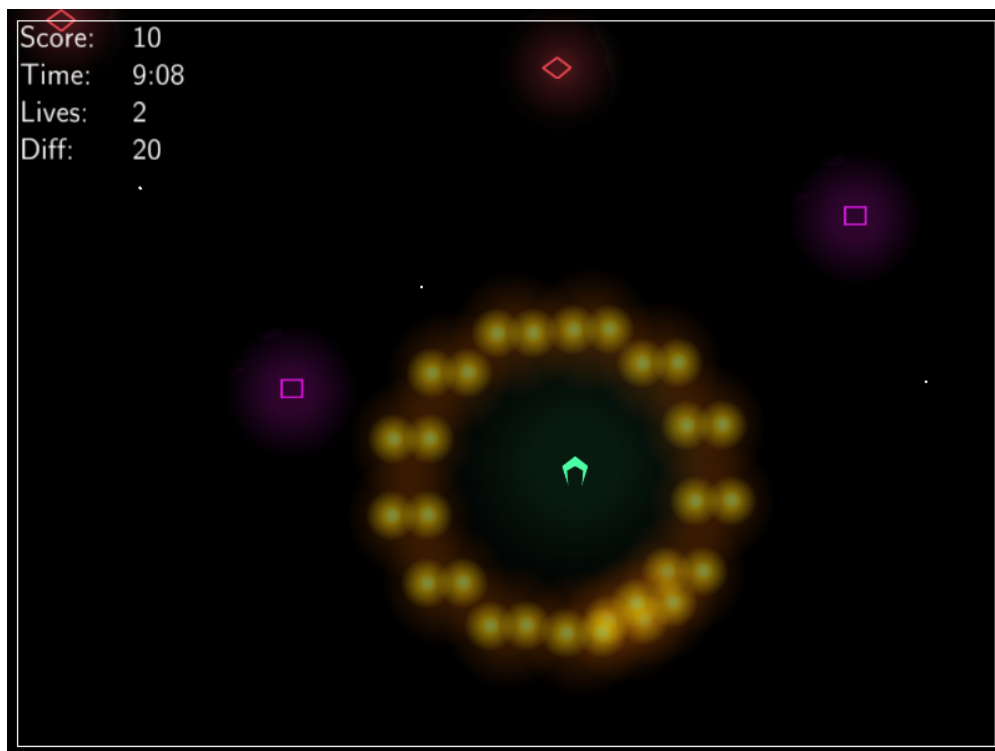
Figure 4. Reduce difficulty bomb

The area bomb was added to address a problem found in preliminary trials showing players often died shortly after making the game too difficult. This situation had to be addressed as it removed the only game state that required users to reduce difficulty. The second adjustment was an addition of a slow but consistent increase of one difficulty point every 5 seconds. Preliminary tests showed that this feature help players understand the concept of changing difficulty.

Affect Model

A mental model similar to Flow—task challenge verses skill level—was used in this experiment to articulate player's mental state from their physiological responses. The model describes the fundamental, non-linear relationship between physiological states and task performance known as physiological activation (Andreassi, 2006). Here, the level of task performance rises with an increase in physiological activity up to a certain point that is optimal for a given task; any further increases in activity would degrade performance (Andreassi, 2006; Kahneman et al., 1993; Portas et al., 1998). This non-linear relationship is similar to the connection between arousal and task engagement. Arousal is the intensity of physiological activation or level of generalized stress in an individual (Andreassi, 2006). Boredom or calmness is considered to exist during low arousal levels and anxiety or challenge during high levels of arousal. However, arousal itself cannot decipher whether or not an individual is highly engaged (flow) or frustrated. For example, if the player's assessment of difficulty was only classified by arousal, then the affect model would be unable to distinguish between the mental states of frustration and flow since the optimal arousal level for the task is unknown and both mental states exist in elevated levels of arousal. This was an important distinction to make since players in the frustration state should the game's difficulty but during flow, increased the difficulty.

Task engagememnt was used to address this issue. Task engagement is the level of cognitive resources allocated to a task. It improves with moderate increase of arousal, but drops dramatically when a state of high excitement is reached (Kahneman et al., 1993). As such, it is not related directly to mental effort (Vicente, Thornton, & Moray, 1987). If only task engagement data were collected, the mental model would not be able to distinguish

between boredom and frustration, as both occur during low task engagement. Game difficulty should be increased during boredom, and decreased during frustration. Gathering physiological indicators of both arousal and task engagement should have allowed plotting of player's assessment of game difficulty correctly to the user's mental states of boredom, frustration or flow.
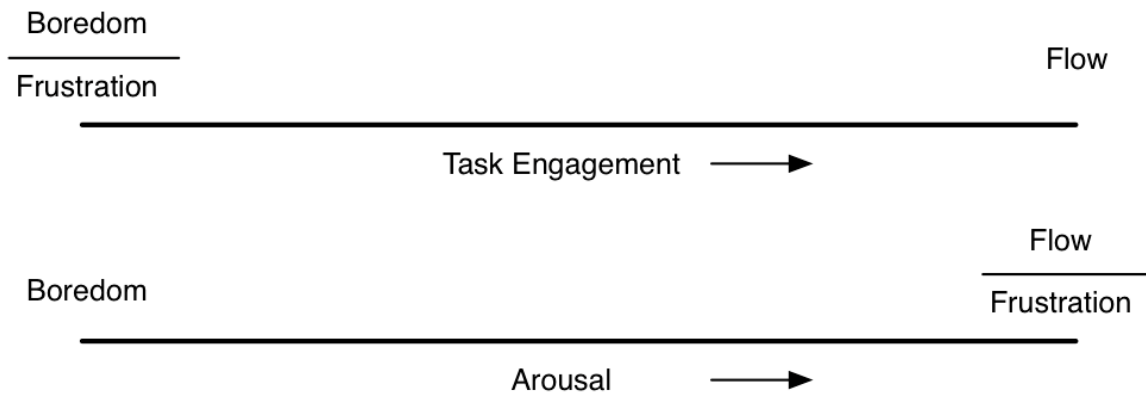
Figure 5. Relationship of task engagement and arousal to affect

Arousal

For this experiment, arousal data were gathered through participant's electrodermal activity (EDA) and heart rate (HR). EDA responds to emotional stimuli such as music, observed violence, and erotic stimuli (Allanson & Fairclough, 2004). HR has been incorporated previously into computer games that alter the level of challenge in real time (Allanson & Fairclough, 2004; Gilleade & Allanson, 2003). Both, EDA and HR are linear indicators to arousal (Andreassi, 2006; Mendes, 2009). The EDA signal was gathered through two electrodes placed on the skin. A small constant current was driven through them and the skin then behaved as a variable resistor. A voltage develops across the electrodes and application of Ohm's law was used to calculate the effective resistance of the skin. (Allanson

& Fairclough, 2004). HR was gathered through electrocardiograms (ECG) which are readings of electrical activity of specific fibers controlling the contractions of the heart and can be used to infer the body's autonomic system (Andreassi, 2006). The signal is a series of waveforms consisting of 5 waves (P, Q, R, S, T) which are characteristic of specific events of the heart (Andreassi, 2006). The QRS complex within the ECG signal is the depolarization just prior to ventricular contraction, which leads to a heart beat. The frequency of successive QRS complexes is the heart rate (Andreassi, 2006).

Task Engagement

Task engagement was collected through heart rate variability (HRV). HRV is correlated with task engagement (Rowe et al., 1998) and has been shown to respond within seconds to cognitive workload (Aasman, Mulder, & Mulder, 1987; Coles & Sirevaag, 1987; Rowe et al., 1998). It is also one of the most common transformations of ECG data for inferring cognitive state (Mendes, 2009). HRV can be analyzed using the root mean square of successive heart beats (Mendes, 2009). Underlying HRV are the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS) (Berntson et al., 1997; Coles & Sirevaag, 1987; Rowe et al., 1998).

Classification Technique

An online classifier was used to establish relationships between player's incremental difficulty appraisals and their physiological data. The classifier was incrementally trained whenever difficulty information was provided though users requests to increase/decrease difficulty. Therefore, performance was assumed to gradually improve overtime as the player entered additional data. This was different than using the typical two experiment procedure

for machine learning—training a classifier on one experiment's data until an acceptable error rate was achieved, and then test its performance on another dataset. Because the psychophysiological classification is initially weak, five data points were required before the adaptation system began influencing the game's difficulty. Once this occurred, the automation continually adjusted the game's difficulty every 2 seconds.

Learning Algorithm

An artificial neural network architecture (derived from an open source neural network package byChhabra, 2010), was used to classify player's physiology to their assessments of game difficulty. Neural networks are effective approaches to distinguish between different levels of task difficulty (Allanson & Fairclough, 2004; Gevins et al., 1998; Laine, Bauer, Lanning, Russell, & G.F, 2002; Wilson & Russell, 2003). Neural networks also have superior predictive capability in comparison to multiple linear regression models (Killough, Crumpton, Calvert, & Bowden, 1995; Zurada, Karwowski, & Marras, 1997), and make minimal assumptions concerning the statistical nature of the data (ie, linearity, normality, homogeneity of variance) (Chen, Kaber, & Dempsey, 2000).

Pre-processing and Discretization of Physiological Input

A two-stage approach was implemented to classify physiological input. The first stage preprocessed the analog physiological signals to discrete classes. The second stage sent the discrete states into a back-propagating multi-layered perceptron neural network. The pre-processing stage was used to first, reduce the risk of under-fitting of the neural network from low numbers of subjective input training data, and second, to filter out possible artifacts collected from the physiological collection device. Each physiological signal was divided

into moving averages and moving deltas of the previous 2 seconds of collected data. Physiological activation indicates that there are different psychophysiological interpretations for different points within a signal's range. A moving average was used as an input to the neural network to provide the current level of physiological signals within each individual's signals range. Current changes within signals (deltas) were used to indicate each signal's variability to the neural network. Each physiological signal's mean and delta were discretized into eight equally sized states within the current known range of a signal. Each signal range was updated continually as data was collected.

Network Organization

The artificial neural network organization had 6 inputs and 1 output. It used 2 layers: 1 hidden layer of 6 sigmoid neurons and 1 output neuron. Preliminary trials suggested a single layer of each input signal is sufficient for classification of physiological patterns. Training of the network was performed through back-propagation of network weights using player's difficulty appraisals as training data. This information was provided as either a 0—user requested decreased difficulty or 1—user requested increased difficulty. The inputs to the network were the discrete 2-second moving means and deltas of player's HR, EDA, and HRV.

Adaptation Software Libraries

A generalized architecture was created for the adaptation's software structure. The flexible system allowed for multiple types of signals, classification techniques, and updating techniques. The system was organized into three distinct libraries. The Signal library was a modular organization of different inputs into the system. The Classifiers library was a set of

multiple classification algorithms to categorize data collected through the Signals library. The Agent library manages the integration of the classifiers with the data signals. Figure 6 indicates the organization of structures within the software to capture the data.

Sensors and Signals

The Signal library provides the interfaces and implementations of various signals to be used within an adaptive system. This library is split into two distinct functionality groups, Sensors and Signals.

The Sensors provided actual collection of data and are organized into three groups; device sensors, dynamic sensors, and simulated sensors. The difference between sensor types is based on how the actual signal data are generated. Device sensors, as the name would indicate, collect data from specific devices such as specific physiological data collection equipment. Dynamic sensors provide a mechanism for collecting data generated in other software, such as specific application button presses or avatar movement. Simulated sensors allow for signal data to be predefined and generated from within the sensor. These sensors are useful for creating test sensors or loading data collected from previous experiments. All sensor classes were adopted from similar C++ virtual interfaces so all sensors can be interchanged with one another.

The second group, Signals, is a set of stackable algorithms which can be applied on top of the different sensor types. The signals are stackable in the sense that all signals can be used as inputs to all other signals. This allows construction of a basic set of filters and transformations to be combined for complex processing on a single input sensor. As an example, a device sensor gathering ECG data for interpretation of HR had two basic signals

stacked. The first was a QRS-detection and feature extraction algorithm. The second signal

stacked on top gathered basic frequency data transforming the output of the QRS detection

signal into frequency information. Some signals such as the QRS detection signal were for

specific use but others, such as moving average signals or spectrum analysis signals could be

applied in various ways. Signal transformations could become much more complex including

Fast Fourier Transformations signals, auto regressive analysis signals, and geometric

matrices transformations run on dedicated graphic hardware. As with the sensors, all signals

conform to similar interfaces and were interchangeable.

Classifiers and Agents

The Classifiers library provides interfaces and implementations of multiple

classification algorithms to classify data collected through the Signal library. The artificial

neural network used for this study was implemented through this interface.

The Agent library manages the updating and integration of classifiers with

asynchronous data signals. Signals are collected from multiple sensors at sampling rates

different than the application and the classifiers which use them. In the most basic form,

agents established a schedule for updating the classifiers on the signal data by resolving the

different timings between the sensors and classifiers. This could have drastic implications on

the nature of the signal classification. For example, physiological sensors could be provided

at a much higher rate of data sampling than classification algorithms can process. If a

classifier requires a single input data set for each training data set, then the agent must

resolve the timing differences between the training signal data and the input signal data. It

was possible for training data sets to be ignored in the event no input signals occurred within

a relative timeframe.
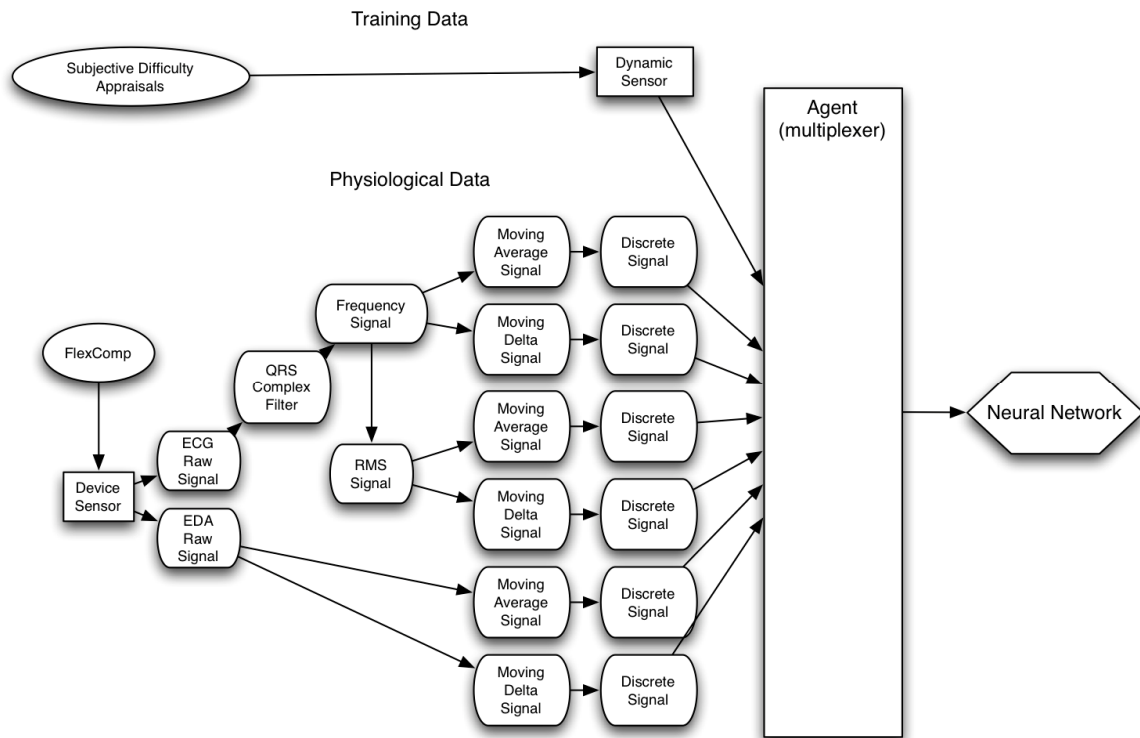
Figure 6. Signal transformations within the adaptation engine

Hypotheses

The following task-related parameters were used in this study: (1) task performance, which is the highest score a player gains; (2) task challenge, which is the highest difficulty attained; (3) subjective input frequency, which is the amount of difficulty adjustments made by the player, and (4) task engagement, which is the level of user's focus or attention attributed to a task evaluated through HRV.

H1. The individualized biocybernetic system will not lead to an increase in maximum task performance.

H2. The individualized biocybernetic system will not lead to an increase in maximum task challenge.

H3. The individualized biocybernetic system will not lead to a decrease in the frequency of subjective inputs.

H4. The individualized biocybernetic system will not lead to an increase in task engagement.

Experimental Procedure

A repeated measures within-group study was used to evaluate the performance of the individualized biocybernetic system. The Institutional Review Board (IRB) at Iowa State University approved this experiment prior to working with human subjects. Pre-test setup involved participants signing an informed consent form, completing a demographic survey, and then allowing baseline physiological reading to be taken.

The experiments included two settings of video game trials: 1) The adapt (experiment) group: here the video game difficulty was adapted by the neural network

classifier. 2) The non-adapt group: Here the neural network classifier did not adapt the game difficulty. It should be noted that while only the adapt group had the game difficulty adapted by the software, participants during both types of trials manually provided difficulty appraisals.

Participants were tasked with 5 trials of 6 minutes each with a 3 minutes break between trials. Each subsequent trial was rotated between the adapt group and the non-adapt group. As such, all participants participated in at least two trials adapted by the individualized biocybernetic system. Participants were given 5 lives at the beginning of each trial. If players lost all lives within the 6 minutes, 5 new lives were given, the game score was reset to 0, and the remaining time was played. After completion of the five trials, each participant completed a post survey related to the games' events. Figure 7 depicts a participant playing the game while connected to the physiological equipment.

Figure 7. Participant playing the game

Apparatus

All trials were run on a 42-inch LCD display located three to four feet from the

participant's viewing position. The ECG and EDA input data were gathered with a

FlexComp physiological sensor (Thought Technology: Montreal, Canada) at a sampling rate

of 2048 Hz. Updating of the adaptation software occurred at a frequency of 10 Hz. ECG data

was collected from three electrodes—positive, negative, and ground—which were placed on

the chest of the participants, so the positive and negative electrodes spanned the heart. EDA

data were gathered through two sensors that were placed on the subject's left middle and ring

fingers. An Xbox360 controller was used for the game controls. All processing of the game

and the adaptation software were run on a 3 ghz Core 2 Duo with a NVidia Quadro 1800

graphics card. Game sounds and music were provided from a 5.1 Logitech speaker system.

Software Dependencies

The modular engine was developed in C++ with Visual Studio 2005 and exported as

a python library using the SWIG library. A modified version of a single scan algorithm for

QRS- detection and feature extraction algorithm was used to detect R-R intervals from the

ECG data (Engelse, 1979). Software developed to access physiological data from the

Flexcomp device used Thought Technology's C++ TTAPI. The video game was written in

Python 2.5.2 using Panda3D 1.6.2. The PyGame library was used for interfacing the xbox360

controller to Panda3D.

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Demographic Analysis

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Demographic data was collected at the onset of experimentation; instrumentation of

classifier and gameplay variables were collected during each participant's interaction with

the software and a post questionnaire was given to assess the participants' experience after the experiment.

Data in the demographic survey captured general demographical information, perceived life stress and general video game experience. The perceived stress questions were taken from the perceived stress scale (PSS) (Cohen, Kamarck, & Mermelstein, 1983). Its use was to investigate the relationship of the subjective appraisals entered with a participant's general psychological tendencies. The questionnaire itself does not have a scale classifying level of stress, however a national poll of 2,387 respondents provided national means and standard deviations on which to rate subject's stress levels (Cohen & Williamson, 1988). Participants were classified into groups of low, medium and high stress. Low was one standard deviation or below the national mean for participant's age group. The medium group consisted of participants within one standard deviation of the mean for their age group. The high stress group was one standard deviation or above. However, no participant in this study fit into the low stress group.

Evaluation Procedures

Classifier performance

Instrumentation of the artificial neural network captured the difficulty appraisals provided by participants, the discrete physiological inputs, and the network's mean squared error (MSE) for every back-propagation performed. The MSE is a functional assessment of the artificial neural network predictions. Since the adaptation occurred after 5 subjective inputs, most of the back-propagations used to learn the new subjective inputs occurred at the same time as the adaptations that used them. So, both the average of all MSE and all final

MSEs are accessed. The final MSE provides indication of the general performance of the classifier while the total average will indicates the actual error rates of the predictions made during adaptation.

System Performance

The methods used to evaluate the individualized biocybernetic systems were related directly to the four hypotheses under examination. Data collected include the raw ECG, EDA, HR and HRV. All data were captured at their respective collection rates. The actual game data captured consisted of game difficulty, game score, and subjective appraisals. Game difficulty was the rating of 0 to 100 of the level of task challenge that the participants can endure. Game score is the general task performance variable in the video game task.

The subjective inputs reflect the amount of effort participants applied to the task difficulty. This metric provided a general assessment of the participant's attention to the difficulty of the game. This data was compared to the perceived life stress groups gathered in the pre-experiment survey to evaluate whether the subjective inputs reflected the general perceived stress of participants. Through intuition it was believed that higher stressed participants would decrease difficulty more often than lower stressed participants . Additionally, it was assumed that lower amounts of total subjective inputs indicated the player's approval of the game difficulty either through conscious appraisal or high engagement with the game. It was believed that success of the adaptation system occurred if participants were engaged enough with the game to forget providing subjective input.

Pair-wise comparisons of adapted trials with non-adapted trials were used to evaluate the experiment data. One-tailed pairwise t-tests were implemented to evaluate significant

differences. For non pair-wise tests such as comparisons between stress groups, the significance of the differences was calculated through t-tests using homeostatic variances.

Differences in experiment data comparing the 2nd and 3rd trials with the 4th and 5th trials were also evaluated to determine the change of performance over successive trials. Results from the participants' first trial were not used, Since the first trial was only used for training and user adjustment. To ensure all equal distribution of adapt and non-adapted trials, all participants in the 2nd and 3rd trials received one trial with game difficulty adapted by individualized biocybernetic system and one trial without. Half of the participants received the adapted trial on the 2nd trial and the other half for the 3rd trial. The 4th and 5th trials followed the same procedure. A significance criterion of p=0.05 was used throughout the discussion of results.

CHAPTER 4. RESULTS

Inferential Statistics

A total of 25 people (7 female, 18 male, ages=19 to 46, mean=24 years; standard deviation=6.6 years) participated in the study. Records for three participants were omitted: two due to a software bug, and the third after discovering that a "bomb hack" in the gameplay enabled the participant to bypass the game's challenge and score maximum points without "dying".

The results of the analysis are provided in the following tables: Table 2 provides level of stress and general game experience. Table 3 provides the error rates for the artificial neural network used to classify physiological patterns to subjective appraisals.

Tables 4 and 5 provide differences in performance across experiment groups and sequential trials. Top score indicates the maximum score attained and is the variable evaluated for H1. Top difficulty is the maximum difficulty attained and is the variable evaluated in H2. Subjective input frequency is the mean rate of inputs provided per second. It is the major data point referenced for H3. Table 6 provides game performance differences between 2nd and 3rd trials and the 4th and 5th trials. This table provides information on how participant's learning of the game influences the performance rate of the adaptation system. Tables 7 and 8 summarize physiological signal differences between trials 2 and 3 and trials 4 and 5, respectively. Both the average and maximum statistics are provided.

Figures 8 through 13 present the differences between participant's performances during adapted and non-adapted trials. Figure 8 and 9 provide differences of top score for different trials. Figures 10 and 11 provide group differences on the top difficulty attained by

participants. Figures 12 and 13 provide differences on frequency of subjective inputs as entered by participants. The X-Axis for all graphs are the subject ID's used in the experiment (E01, E02, etc.).

Tables 9 to 13 summarize the relationship between subjective inputs and the stress groups. These tables provide insights into the relationship between subject's general perceived stress and use of the adaptation system. Table 9 shows the difference in total subjective input in trials 2 and 3 compared against total subjective inputs in trials 4 and 5. Results within table 9 augment the subjective input frequencies collected between experiment groups found in tables 4 and 5 to show the change in total subjective inputs between successive trials. Table 10 shows the differences in subjective inputs types between experiment groups. Table 10 indicates how the adaptation system changes the type of difficulty inputs provided by participants.

Tables 11 and 12 expand the results of tables 9 and 10 into differences between stress groups. Table 11 indicates total subjective input differences between stress groups. Table 12 provides the composition of subjective input types between medium and high stress groups. Table 12 indicates the differences in the amount of subjective inputs types entered between perceived stress groups. Table 13 provides general ratios of different types of subjective inputs against stress levels and experiment groups.

Table 2. Participants' stress and game experience (n=25)

	Low	Medium	High
Perceived Stress	0	16	9
Game Experience	9	11	5

Table 3. Error rates of the neural network

	Total	During Adapt Trials	During Non-Adapt Trials
Average Mean Squared Error	0.16	0.16	0.16
Final Mean Squared Error	0.13	0.14	0.14

Table 4. Performance results of trials 2 & 3 (n=25)

Trials 2&3	Adapt Group		Non-Adapt Group	
	Mean	Stdev	Mean	Stdev
Top Score	435902	629425	298234	290404
Subjective Input Frequency	0.52	0.85	0.25	0.32
Top Difficulty	47.44	13.62	41.48	11.93

	Difference	Percent	Stdev	p-Value
Top Score	137667	46.16	523024.81	0.10
Subjective Input Frequency	0.27	105.58	0.80	0.05
Top Difficulty	5.96	14.37	11.90	0.01

Table 5. Performance results of trials 4 & 5 (n=25)

Trials 4&5	Adapt Group		Non-Adapt Group	
	Mean	Stdev	Mean	Stdev
Top Score	633625	663393	540336	596701
Subjective Input Frequency	0.65	0.94	0.46	0.69
Top Difficulty	56.31	19.15	45.36	16.03

	Difference	Percent	Stdev	p-Value
Top Score	93288	17.27	292781	0.06
Subjective Input Frequency	0.18	38.84	0.47	0.03
Top Difficulty	10.95	24.15	21.55	0.01

Table 6. Performance difference between trials (2-3 & 4-5) (n=25)

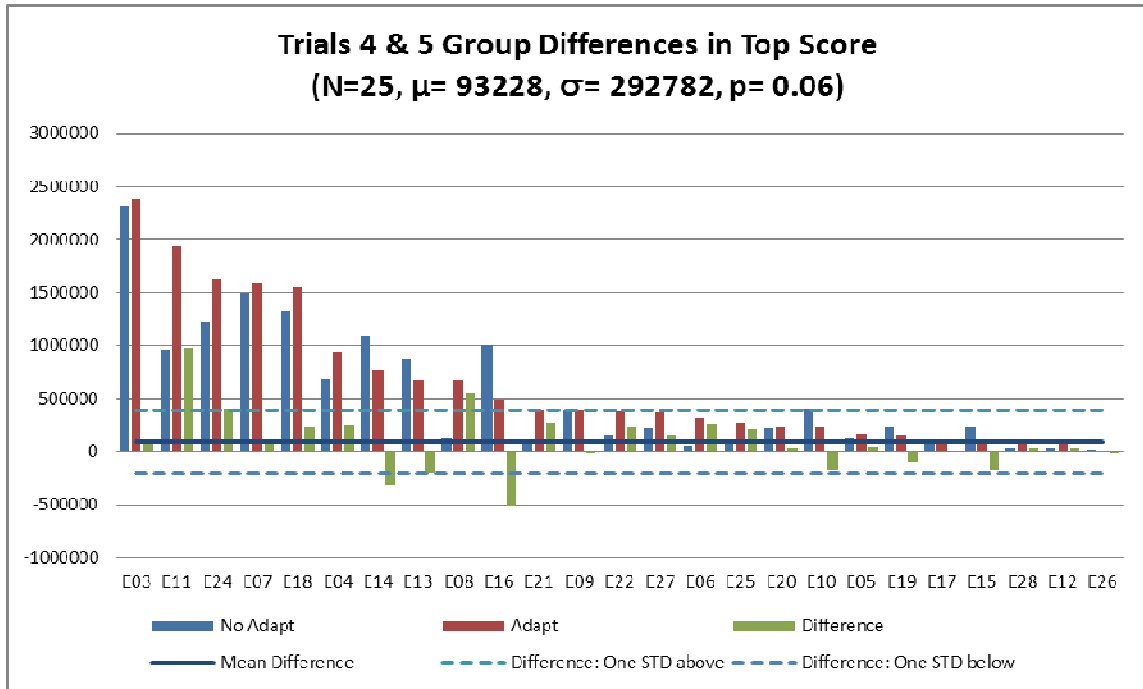|	Difference	Percent	Stdev	p-Value
Adapt Top Score	197723	45.36	515181	0.03
Non-Adapt Top Score	242102	81.18	444537	0.01
Adapt Top Difficulty	8.87	20.67	14.00	0.00
Non-Adapt Top Difficulty	3.88	10.30	10.06	0.03

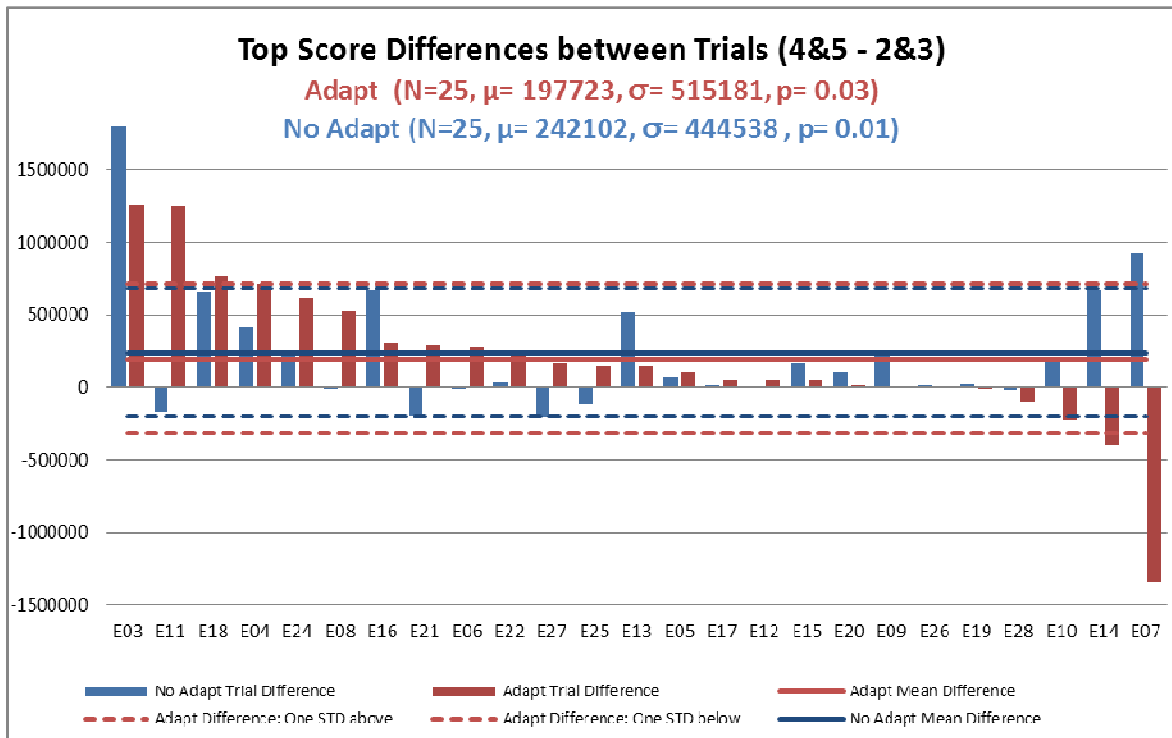**Figure 8. Trials 4&5 Top Scores Differences**

Figure 9. Top Score Differences between Trials 2&3 and Trials 4&5
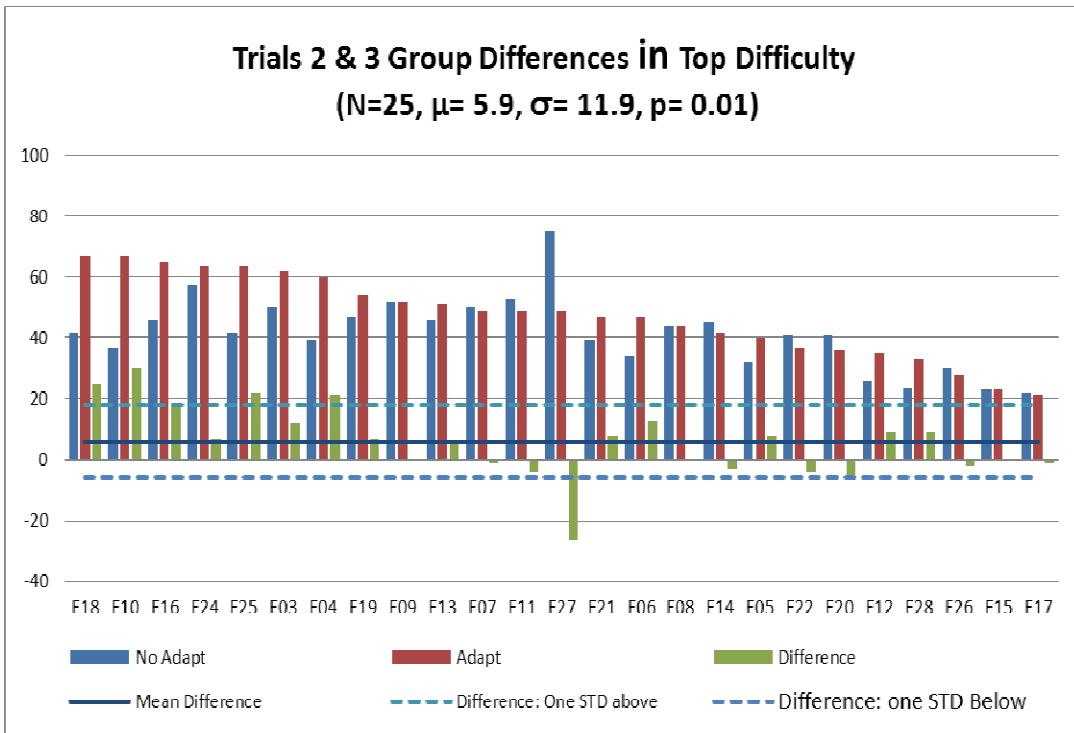
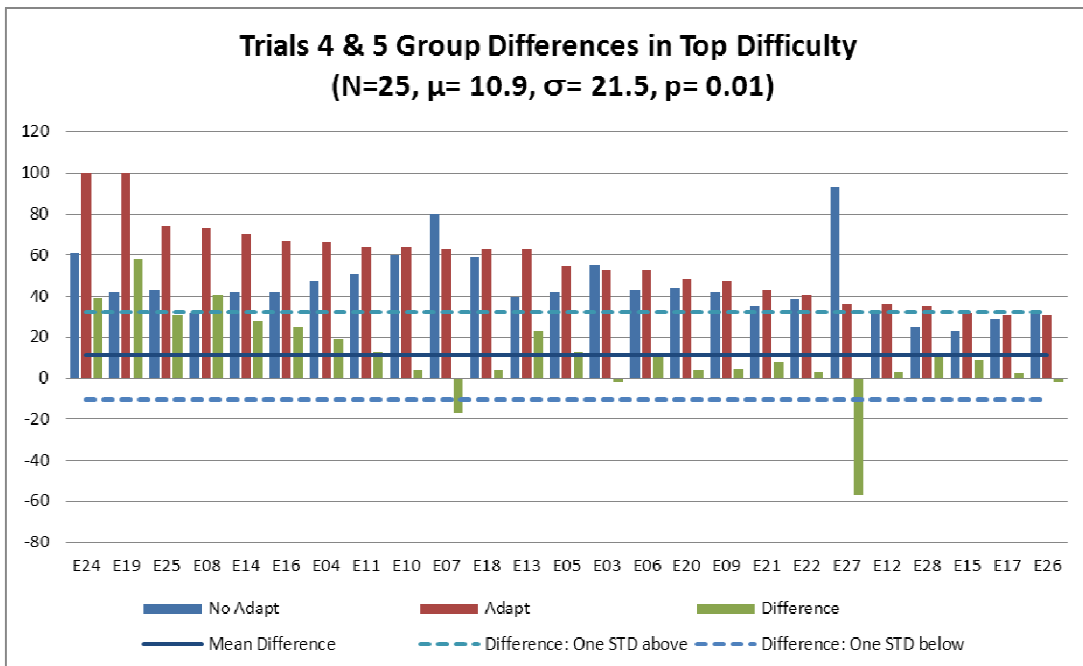**Figure 10. Trials 2&3 Top Difficulty Differences**

Figure 11. Trials 4&5 Top Difficulty Differences
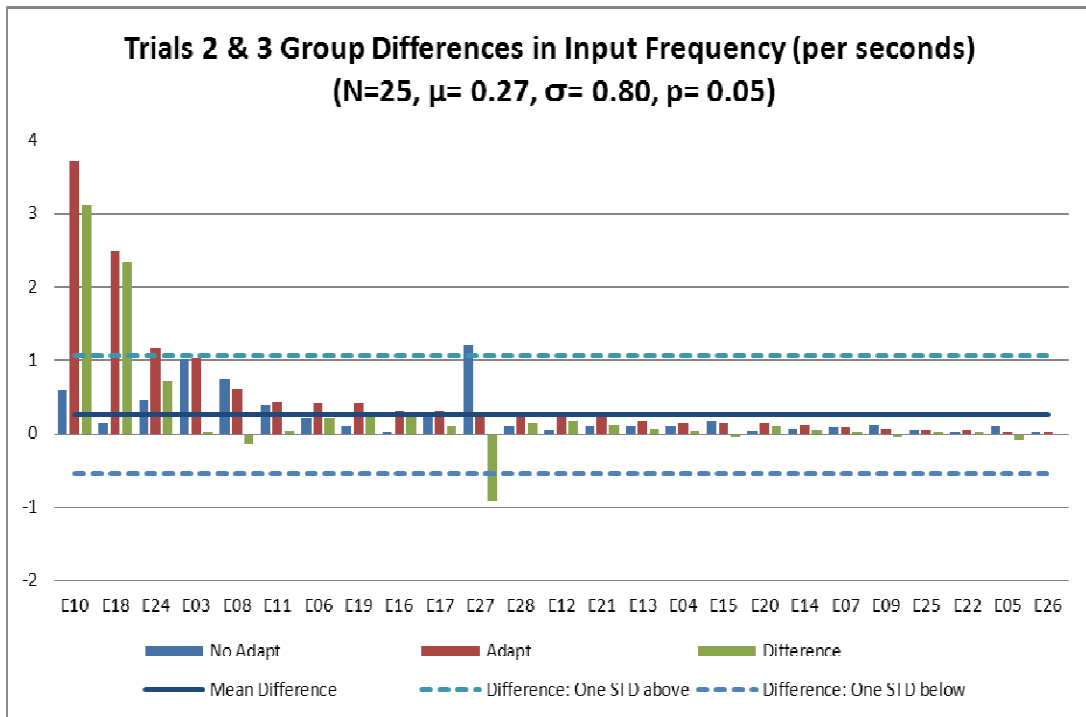
Figure 12. Trials 2&3 Input Frequency Differences
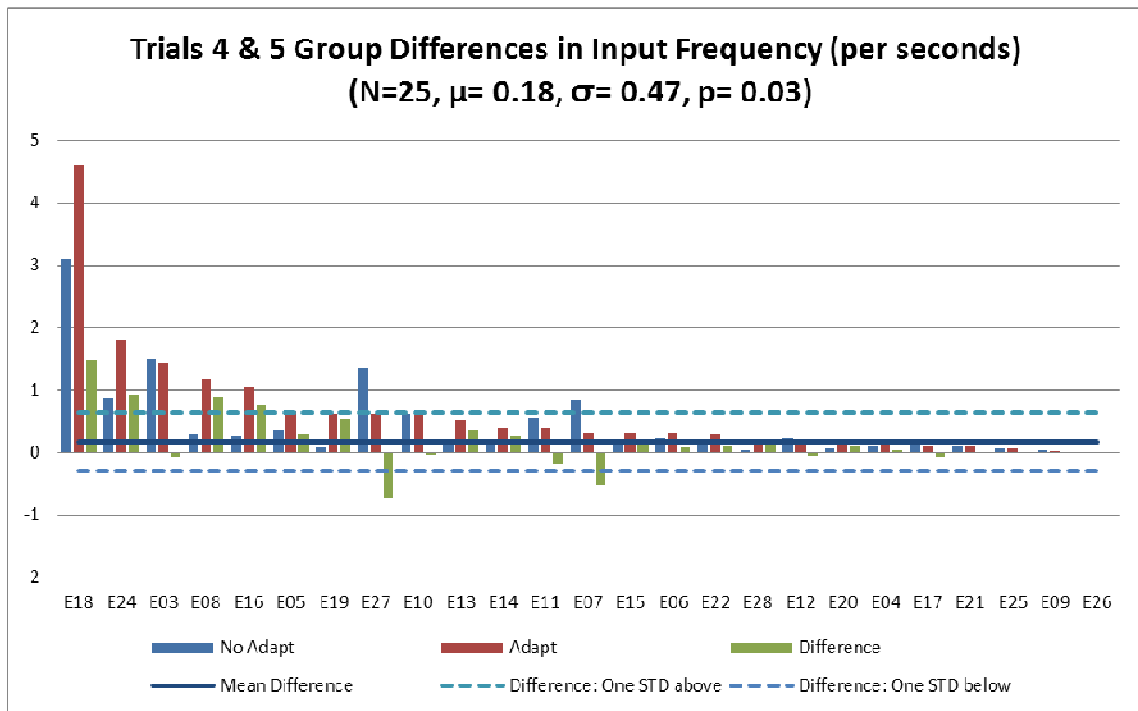
Figure 13. Trials 4&5 Input Frequency Differences

Table 7. Physiological results of trials 2 & 3 (n=25)

Trials 2&3	Adapt Group		Non-Adapt Group	
	Mean	Stdev	Mean	Stdev
Heart Rate Average (beats per minute)	6.18	13.65	6.88	15.46
Heart Rate Max (beats per minute)	43.21	34.467	37.591	33.72
Skin Conductance Average	343	410	305	366
Skin Conductance Max	499	532	438	477
Heart Rate Variability Average	0.029	0.0001	0.030	0.0005
Heart Rate Variability Max	0.032	0.0021	0.031	0.0018

	Difference	Percent	p-Value
Heart Rate Average (beats per minute)	-0.7	-10.15	0.06
Heart Rate Max (beats per minute)	5.61	14.93	0.19
Skin Conductance Average	38.58	12.65	0.03
Skin Conductance Max	61.34	14.00	0.05
Heart Rate Variability Average	-0.0007	-2.34	0.00
Heart Rate Variability Max	0.0005	1.67	0.08

NOTE: differences are changes from baseline physiological data gathered before game deployment

Table 8. Physiological results of trials 4 & 5 (n=25)

Trials 2&3	Adapt Group		Non-Adapt Group	
	Mean	Stdev	Mean	Stdev
Heart Rate Average (beats per minute)	4.52	17.13	5.57	18.50
Heart Rate Max (beats per minute)	42.78	38.845	30.942	27.18
Skin Conductance Average	391	412	400	439
Skin Conductance Max	564	526	558	539
Heart Rate Variability Average	0.030	0.0007	0.030	0.0005
Heart Rate Variability Max	0.032	0.0019	0.032	0.0019

	Difference	Percent	p-Value
Heart Rate Average (beats per minute)	--1.06	-18.95	0.61
Heart Rate Max (beats per minute)	11.84	38.25	0.06
Skin Conductance Average	-9.11	-2.28	0.31
Skin Conductance Max	5.85	1.05	0.42
Heart Rate Variability Average	-0.0008	-2.67	0.00
Heart Rate Variability Max	-0.0001	-0.20	0.44

NOTE: differences are changes from baseline physiological data gathered before game deployment

Table 9. Total subjective input differences between trials (2-3 & 4-5) (n=25)

	Difference	Percent	p-Value
Adapt	-62	-27.84	0.22
Noon-Adapt	-23	-18.02	0.34

Table 10. Difference between *Decrease Difficulty* & *Increase Difficulty* inputs (n=25)

	Difference	Percent	p-Value
All	-9.88	-6.18	0.23
Adapt	-9.90	-9.82	0.16
Non-Adapt	0.02	0.03	0.50

Table 11. Total subjective inputs differences between stress groups (High – Medium) (n=25)

	Difference	Percent	p-Value
Adapt	-55	-26	0.26
Non-Adapt	-20	-16	0.35

Table 12. Difference of (*Decrease Difficulty* - *Increase Difficulty*) inputs between high and medium stress groups (n=25)

	Difference	Percent	p-Value
All	41	15.46	0.07
Adapt	31	10.33	0.07
Non-Adapt	10	6.12	0.19

Table 13. Subjective input ratios of *Decrease Difficulty* / *Increase Difficulty* (n=25)

	High Stress	Medium Stress
Adapt	0.50	0.39
Non-Adapt	0.60	0.54

CHAPTER 5. FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

This research was conducted to establish the viability of a possible alternative to system adaptations conducted with generalized psychophysiological relationships. The results indicate that there are significant task performance increases when using the individualized biocybernetic system. The results also demonstrate significant potential for future research.

Findings

Relationship of Subjective Input to Perceived Stress

Perceived stress had a moderately significant effect on the type of subjective inputs provided by participants. Table 12 indicates participants that were classified with high perceived stress had a significant increase in amount of "decrease difficulty" subjective inputs in comparison to the medium stress participant group. High perceived stress participants had, on average, 31 additional "decrease difficulty" inputs (a 10% increase, p=0.07) than "increase difficulty" inputs during adapt trials and an insignificant change during non-adapt trials. This suggests that high stress individuals are more likely to decrease the game difficulty than less stressed individuals. This result is consistent with intuition that high perceived stress should relate to more decreased difficulty adjustment. It also indicates the difficulty inputs were entered as intended for the experiment and not for other techniques to increase points scored.

Performance of the Artificial Neural Network

Table 3 indicates that the overall neural network error rate was 0.17. There was no significant change between the adapt and non-adapt trials. So, on average the neural network

predictions contained a variance of 0.17 from actual subjective appraisals. Compared to error rates of generalized learning algorithms, this error rate is considerably high. Preliminary trials had suggested error rates near 0.001, which is several magnitudes of order lower than was actually achieved. However, the results of increased performance when using the biocybernetic system suggest the predictions were effective, but not optimal.

This error tolerance was possibly due to the way the biocybernetic system adjusts the difficulty by small increments. A single prediction only changed the game difficulty by 1 point which was out of a range of 100. So a single change in difficulty had a limited effect on the gameplay. Only the sum of multiple predictions would have a significant influence on the difficulty level. Since the error rate shows the classifier was correct more often than not, the total effect of the predictions was more likely to be correct. In addition, participants could provide quick and incremental feedback whenever a prediction was wrong, thus nullifying any incorrect predictions from adding together. Further research should investigate the effectiveness of different adaptation parameters using varying prediction error rates.

Performance of the Individualized Biocybernetic System

Table 5 show significant differences in both game performance and task difficulty measures between experiment groups (adapt and non-adapt). The 4th and 5th trials showed a moderately significant increase in top scores (17 %, p=0.06, Figure 8) and a significant increase in top difficulty (24%, p= 0.01, Figure 11) attained in trials using the adaptation over non-adapted trials. Therefore, hypotheses H1 and H2 are rejected.

Tables 6 reveal that the top score increased in trials 4 and 5 over trials 2 and 3 for both adapted (45%, p=0.03, Figure 9-red) and non-adapted (81%, p=0.01, Figure 9-blue) groups. However, the differences between these groups in earlier trials (46%, p=0.10, Table 4, Figure 8) were reduced in trials 4 and 5 (17%, p=0.06, Table 5). This difference indicates that while the adaptation system enhanced performance for all trials, the performance gain based on the adaptation system decreases in subsequent trials. One possible conclusion is that the adaptation system has a greater value as an augmentation for increasing learning speed rather than a general tool for increasing user performance. However, the reasoning and the extent of the individualized biocybernetic system as a learning device are beyond the scope of this research.

Another potential explanation arises from task difficulty data in tables 4 and 5. The decrease in the separation of performance between the adapt and non-adapt groups over sequential trials may be caused by participants' play strategies, where the participants became more risk-seeking. Table 4 indicates that the 2nd and 3rd trials had an increase of max difficulty (5.96 points p=0.01, Figure 10), which increased further in trials 4 and 5 (10.95 points, p=0.01, Figure 11). This increased change in max difficulty may indicate that later trials exceeded an optimal difficulty threshold for scoring points. The increased difficulty may indicate that subjects became over-confident in setting the difficulty which ultimately affected their performance. It is quite possible that subjects viewed the adaptation adjustments as conservative, even though the results show that the performance significantly increased with the adaptation system. Additional research on participant's decision behavior is needed to evaluate the cause for participants' change in motivations in later trials.

Physiological Differences

There was an insignificant change in HR average between the adapted and non-adapted group (-1.056 beats per minute, p=0.26, Table 8). Interesting though is the moderately significant increase in max HR during adapted trials over non-adapted trials (11.86 beats per minute p=0.06, table 8). This is an increase over earlier trials when the max HR difference between groups was insignificant (5 beats per minute; p=0.18). These data further support the potential explanation that subject's risk seeking caused additional stress by over extending their difficulty level in later adapted trials. This should be further validated with an appropriate instrument for risk seeking propensity.

Table 8 indicates a sustained reduction of HRV for trials 2 and 3 (2.3%, p=0.00) and trials 4 and 5 (2.6% p=0.00). This suggests an increase in task engagement in the adapted trials. However, the moderate percentage change does not allow for rejection of the hypothesis H4 for task engagement.

Subjective Input Characteristics

A significant increase of subjective input was provided for adapted trials during trials 2 and 3 (105%; p=0.05, table 4, Figure 12) and trials 4 and 5 (38.8%; p=0.03, table 5, Figure 13). This was unexpected as the intended effect of the adaptation system was to reduce subjective input. It was expected that an effective adaptation system will reduce the cognitive demand (or attention) of appraising the difficulty of the game. This type of behavior was not observed. Therefore, the results failed to reject H3. There are multiple possible explanations for this behavior. First, it is possible that the perceived conservative nature of the system's adaptations affected subject's input behavior, leading to an increase in subjective input. It is

also possible that the adapted trials acquired an increase of cognitive resources for both the primary game task and the subjective assessment. So, subjects were more aware of their ability to enter subjective inputs during adapted trials. This explanation is more appropriate considering that both game task performance and the subjective input increased in adapt trials. Further research evaluating cognitive demand may provide more appropriate results in this area.

Limitations

The overall data suggest that individualized biocybernetic adaptation leads to a reduction in perceived difficulty. However this conclusion cannot be extended beyond this experiment's task parameters. Adjustments to the game's parameters can possibly alter the way the adaptation system affects players' performance. It is possible that the game's difficulty progression was set too high. There may also have been complications resulting from the characteristics of the gameplay such as the bomb to reduce game difficulty.

Summary

This research provides a proof of concept for the individualized biocybernetic system design. The general framework has been established and a set of extendable software libraries have been adopted and implemented. The system requires no earlier knowledge about individual's physiological relationships to mental states in order to provide adaptation. The system takes into account the individualized nature of physiological signals and eliminates the possibility that physiological specificity will compromise adaptation. Additionally, all physiological patterns are trained on subjective data gathered at time of

experience. Because of this, the possibility of duration neglect or the peak-end rule affecting the subjective appraisal entered is not an issue.

A within-group study was conducted on the performance of the system. The study confirmed the viability of the individualized biocybernetic systems for improving a player's performance when adapting video game difficulty. The results provide evidence of significant task performance increase and higher attained task difficulty when players interacted with the game using the adaptation system. The results also demonstrate that the subjective appraisals used directly related to the participants' perceived state of stress. The hypothesis of reduced subjective input when using the individualized biocybernetic system was rejected, potentially due to player's implementation of risk seeking strategies.

Recommendations for Further Research

The results of this initial study establish the viability of an individualized biocybernetic system as a possible alternative to system adaptations conducted with generalized psychophysiological relationships. The results indicate multiple positive effects when using the system. However, further research is needed on alternative input signals, subjective inputs, and classification mechanisms. As such, it is recommended that the main output of this study, the adaptation software libraries, be employed across various applications that require individualized adaptation and tests be performed to evaluate the system's performance in these alternative contexts.

Alternative signals in both the behavioral and physiological arenas should be evaluated. In general, physiological signals have attributes that are beneficial for adaptation, but the hardware required is far from ubiquitous. This hardware limitation reduces the

number of applications in which physiological signals may be used. Behavior inputs such as traditional inputs entered to computers through mouse and keyboards contain a larger user base. Further evaluations are needed on performance differences between adaptations from physiological signals to adaptations using behavioral signals.

Similarly, additional studies should be conducted to evaluate multiple classification strategies to improve the prediction rate of subjective input. The results of the present study indicate that the two-layered, pre-processed neural network had a considerably large error rate when predicting Boolean subjective appraisals from six different physiological signals. Evaluation of the neural network organization, as well as analysis of alternative learning mechanisms, could provide increased viability of this individualized adaptation. The data collected from this experiment should be used for preliminary studies in this area.

Interesting future research might investigate the dynamics between classifier prediction rates and various task adaptations. Interesting questions include: what task adaptations are more fault tolerant? Is there a possible function establishing a required minimum classification error rate for different task adaptations in order to avoid perception by users? For instance, it appears that smaller, more incremental changes in tasks such as the adaptations performed in this study are more tolerant of prediction errors than are more significant adaptations which have greater effect on the task.

Another possible research question that stems from this investigation is what effects do task adaptations from different machine learning algorithms have on the overall performance of the algorithm's learning rate. This study's results show an insignificant difference in error rates between adapted trials and non-adapted trials. However, a mechanism with lower prediction error may show a more noticeable improvement in the

algorithm's learning rates through task adaptation than without. Such a metric might be effective at establishing the level of synergy, or communication level, of human computer interaction from the computer's perspective.

A benefit of the individualized biocybernetic system is its ability to adapt to changes in psychophysiology. Future research should investigate the use of these systems for applications in which psychophysiological patterns can change. These applications include: adaptive software for populations with non-typical psychophysiological patterns such as individuals with chronic stress disorders; and high stress applications where psychophysiological patterns changes occur due to traumatic physiological events. The system could possibility adapt to traumatic events and provide sustained task performance when such events occur. Applications such as this would tend to revolve around highly stressful and high risk tasks such those of military personnel and first responders.

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APPENDIX A : PRE-EXPERIMENT QUESTIONNAIRE

Note: Survey will be administered via an online survey application (Qualtrics)

Demographic Survey

1. Age:

2. Sex:
   __ *Male*
   __ *Female*

3. What is the highest level of education you have completed?

   a. High School

   b. Associate degree

   c. Bachelors

   d. Masters

   e. PhD

   f. Other: _____

4. Do you play with any type of the computer/video games listed below? (check all that apply)

   ____ Console first person shooters (Halo, Console Left 4 Dead, etc)

   ____ Computer first person shooters (Team Fortress, Computer Left 4 Dead, etc)

   ____ Role-playing games (World of Warcraft, Farmville, etc)
   ____ Arcade shooters (Asteroids, Geometry Wars, etc)
   ____ Third person perspective games (Uncharted, Grand Theft Auto 4, etc)
   ____ Fighting games (Street Fighter, Tekken, etc)
   ____ Puzzle games (Tetris, Snood, Bust-a-Move, etc)
   ____ Racing games (Need for Speed, FZero, etc)
   ____Other:

5. How many hours do you spend playing games:

   ____I do not play games
   Daily:
   ____ Console first person shooters
   ____ Computer first person shooters
   ____ Role-playing games

_____ Arcade shooters
_____ Third person perspective games
_____ Fighting games
_____ Puzzle games
_____ Racing games
_____Other:

Weekly:

_____ Console first person shooters
_____ Computer first person shooters
_____ Role-playing games
_____ Arcade shooters
_____ Third person perspective games
_____ Fighting games
_____ Puzzle games
_____ Racing games
_____Other:

Monthly:

_____ Console first person shooters
_____ Computer first person shooters
_____ Role-playing games
_____ Arcade shooters
_____ Third person perspective games
_____ Fighting games
_____ Puzzle games
_____ Racing games
_____Other:

6. Are you affected emotionally when playing video games?

    a. 1-7 (1 – not at all, 7 – I cry when my character dies)

7. How engaged are you with games while playing?

    a. 1-7 (1- not at all, 7 – I forget to eat meals)

8. Are you maintaining an aerobic exercise routine of 30 minutes or longer?

    a. Yes

    b. No

9. If yes, how often?

    a. more than 3 times a week

    b. 1-3 times a week

    c. once every other week

    d. once a month

    e. Less than once a month

1. In the last month, how often have you been upset because of something that happened unexpectedly?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

2. In the last month, how often have you felt that you were unable to control the important things in your life?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

3. In the last month, how often have you felt nervous and "stressed"?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

4. In the last month, how often have you felt confident about your ability to handle your personal problems?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

5. In the last month, how often have you felt that things were going your way?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

6. In the last month, how often have you found that you could not cope with all the things that you had to do?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

7. In the last month, how often have you been able to control irritations in your life?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

8. In the last month, how often have you felt that you were on top of things?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

9. In the last month, how often have you been angered because of things that were outside of your control?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often

10. In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?

   ___0=never ___1=almost never ___2=sometimes ___3=fairly often ___4=very often