Capturing user engagement via psychophysiology: measures and mechanisms for biocybernetic adaptation

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Abstract: The concept of task engagement is associated with effortful striving to reach a desired goal. This dimension is fundamental for software designed to elicit high quality performance. This paper will review the concept of task engagement, both in the psychological literature and with respect to affective computing approaches, such as biofeedback and the definition of 'flow' states. This paper will briefly describe a series of laboratory experiments designed to explore measures of task engagement based on EEG and cardiovascular measures. These experiments employed a number of manipulations to influence task engagement, e.g. performance feedback, task difficulty and financial incentives. Results demonstrated the sensitivity of EEG measures to cognitive sources of engagement (e.g. mental workload) whilst cardiovascular variables tended to respond to the motivation to achieve. We use these findings to explore how real-time monitoring of engagement may generate adaptive dynamics for software design using a computer game as an exemplar system.

Keywords: PC; physiological computing; BA; biocybernetic adaptation; task engagement; EEG; ECG; computer games.

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1 Introduction

Physiological computing (PC) describes a category of technological systems that capture psychophysiological changes in the user in order to enable and inform real-time software adaptation (Allanson, 2002; Allanson and Fairclough, 2004; Fairclough, 2009). PC systems rely on psychophysiological methods to create a representation of intentional control input or the user state in real time. Transforming psychophysiological signals into control inputs, e.g. left hand vs. right hand, *x–y* coordinates, button presses, represents the domain of brain–computer interfaces (BCI) (Allison et al., 2007). The psychophysiological conceptualisation of the user state may be operationalised with reference to a number of dimensions, e.g. level of mental effort, positive and negative emotions, high vs. low task motivation – this kind of PC system is termed as biocybernetic adaptation (BA). In both cases, real-time psychophysiology is used to capture and to represent an intentional action or state change; the PC system consults this representation to select an appropriate category/magnitude of response. This classification problem has two aspects: accurately representing an intentional action or change in user state and matching this representation to an appropriate software responses. For BCI systems, the challenge is to accurately map input control dynamics, e.g. the relation between psychophysiological change and cursor control. The main hurdles to the development of BA technology are to accurately classify changes in user cognition or emotion using psychophysiology and to ensure an appropriate software response. For example, if the user is frustrated, changes in user state should prompt the presentation of help information; if a player is bored by a computer game, the representation of user state should trigger an increase of game difficulty (Fairclough, 2007; Gilleade et al., 2005). The main challenges in this case are to distinguish target states using psychophysiological measures and to devise an adaptive response i.e. implicit, intuitive and helpful from the perspective of the user. Unlike BCI applications (Allison et al., 2007), the BA approach is essentially passive (i.e. the emphasis of the BA system is on monitoring with no intentionality required on the part of the user); in addition, BA functions at the meta-level of the human–computer interaction (HCI) (i.e. ensuring that the design goals of system interaction are achieved such as: ensuring safety, minimising discomfort and distress, and optimising positive affect) whereas BCI represent an alternative form of input control within the interaction (Fairclough, 2008). In both cases, the cycle of information flow wherein psychophysiological change is transformed into software control may be described as a biocybernetic loop (Pope et al., 1995).

This paper is concerned with the development of BA technology. This category encompasses several existing strands of research/applications, from the control of adaptive automation (Scerbo et al., 2003; Wilson and Russell, 2007) using measures of mental workload to the use of psychophysiology to represent user emotion (Picard et al., 2001). Our aim is to combine two strands from existing research, one focused on BA in the context of cognitive workload and a second derived from previous research on affective computing. We believe both aspects may be incorporated into a broad construct of task engagement i.e. a fundamental dimension of user performance. Task engagement has relevance across a range of software applications where the BA approach may be applied, e.g. transportation, command-and-control, auto-tutoring and computer games.

1.1 Task engagement as a concept

Task engagement is a fundamental dimension of user psychology related to human performance. It has been defined as an "effortful striving towards task goals" (Matthews et al., 2002) and is related to mental effort investment, which has been similarly defined as "energy mobilisation in the service of cognitive goals" (Gaillard, 2001). If a task is cognitively challenging (e.g. increased memory load or multiple sources of attention), it is reasonable to expect mental effort to rise accordingly. A second scenario involves the user being exposed to high task demand whilst simultaneously reducing his or her investment of mental effort. In this example, the user has disengaged from the cognitive requirements of the task (Wright, 2008). Disengagement may occur for a variety of reasons, the user may be tired or bored by the task or at the other extreme – the user may be overwhelmed by task demands of the task and feel unable to successfully achieve a task goals. A state of disengagement is characterised by changes in cognition, motivation and emotion, e.g. reduced cognitive effort directed at task activity, declining levels of task motivation to achieve a given goal and any associated emotional response, such as anxiety, frustration or unhappiness. For example, Burleson and Picard (2004) described a state of 'stuck' that may occur during the learning process to the detriment of user motivation. The definition of this state combines negative affect (e.g. anxiety) with cognitive characteristics (e.g. inability to focus and mental fatigue). This conceptualisation of task engagement concedes the multidimensionality of the concept and questions the extent to which psychophysiology may be used to disentangle cognitive responses from affective ones and vice versa.

1.2 Task engagement as a performance state

Task engagement may be linked to similar psychological concepts related to competitive performance and creative problem solving. From gunning down hordes of ravenous monsters, to driving skilfully around a difficult bend on a race course, states of extreme engagement may be described as flow states (Csikszentmihalyi, 1990). Sometimes referred as being in the zone (Chen, 2007), this state of mind is a desirable experience during game play as it represents a state in which the challenge is at least on par with the player's skill set. Games which provide optimum levels of challenge are more likely to be better received by the gaming community as they avoid undesirable mental states (e.g. boredom and frustration) (Gilleade and Dix, 2004) and promote a positive emotional experience. In models of flow (e.g. Nacke and Lindley, 2008), a person can be said to be in one of four states: bored, apathetic, in flow or anxious. Transitions between states occur as the balance between task demand and the user's skills change. For example, if the player is in state of flow: the demands of the task are said to be at the optimum level for the player's skill level. However, if the player should die and have to restart the level, the skills they have already learnt in tackling the game favour the balance towards the player (i.e. their skill set is greater than the challenge requires) and subsequently, the player will not enter the flow state as easily as before. A similar situation was reported by Chanel and Rebetez (2008) who found that repeated play of the same Tetris challenge showed a decrease in self-reported measures of pleasure. Gilleade et al. (2005) argued that conventional games are not well suited to maintain the optimum level of challenge needed for flow as they are aimed at an ideal player: a player who comes to the game with a given skill set and progresses in a specific manner. Obviously, not all players are alike and do not always follow the playbook envisaged by the game designer, so it is to be expected that players transition between different flow states during play. Given being outside the flow state during play is not seen as being desirable, one design possibility is for games to adapt difficulty in an intelligent and strategic fashion in order to maximise and sustain levels of user engagement (Fairclough, 2008).

1.3 Measures of task engagement

Factors that exert an influence on user engagement and flow states have been described as cognitive or compensatory in nature (Mulder, 1986). In the case of the former category, mental effort is invested in response to changing task demands, e.g. increased multitasking requirement and increased game difficulty. Compensatory effort is important to protect performance under demanding conditions that derive from a non-cognitive source, e.g. boredom, sustained task activity and sleep deprivation. The adaptive logic of the BA system requires a differentiation between distinct categories of user disengagement. If engagement declines during a game because the player is bored, then the appropriate response from the system is to challenge the player. However, a decline of engagement due to excessive game difficulty represents a different category of disengagement and requires a different adaptive response, e.g. to assist the player (Gilleade et al., 2005).

Task engagement can be defined with respect to cognitive activity (mental effort), motivational orientation (approach vs. avoidance) and affective changes (positive vs. negative valence). Mental effort is conceptualised as energy mobilisation in the service of cognitive tasks or goals. At the cerebral level, the electrical activity of the brain may be quantified via the EEG to study how different states of brain activation represent the level of mental effort investment. The topography of EEG activation may provide important information about the specificity and distribution of activation over the cortex. A series of experiments demonstrated that augmentation of theta activity (4–7 Hz) from central frontal sites and suppression of alpha activity from occipital areas were both associated with increased mental effort in response to working memory load (i.e. number of items to be retained in memory) (Gevins and Smith, 2003; Gevins et al., 1998). The pupillary response has a long association with the measurement of mental effort in response to cognitive variables (Beatty, 1982). There is evidence that pupil dilation is greater during the processing of a complex cognitive operation relative to a simple one. The main problem with pupilometry is interference from light adaptation, i.e. for those environments where the level of lighting is not carefully controlled. The index of cognitive activity (Marshall et al., 2004) represents an attempt to quantify small discontinuities in pupil size that are related to cognitive activity. The ICA is derived in a selective manner that minimises the influence of lighting levels. There is an obvious linkage between task engagement and the motivation to successfully achieve a given outcome.

Motivational intensity theory (Wright, 2008) proposes that goal commitment (i.e. the willingness to invest effort into the task) is a function of perceived:

1 task difficulty

2 ability

3 likelihood that successful performance on the task will achieve a desired motive (e.g. monetary incentives, prowess, 'feeling good').

Therefore, if the individual assesses themselves to have the requisite level of skill to achieve success, then effort is invested to achieve task goals. Research into motivational intensity theory has used indicators of sympathetic nervous system (usually systolic blood pressure (SBP)) to describe the 'tipping point' where increased difficulty/reduced perception of ability/reduced perception that the task is worthwhile forces participants to switch from effortful striving for goal success to disengagement and a significant reduction of mental effort (Richter and Gendolla, 2007; Richter et al., 2008). Related research has linked changes in frontal EEG asymmetry to the self-regulation of affect and motivational orientation. In broad terms, the experience of positive emotions is associated with high levels of relative left frontal activity, whereas negative emotions are related to increased relative right frontal activity (Davidson, 2004). There is also evidence that increased left frontal activation is correlated with motivational approach whilst right frontal activation is linked with a motivation disposition in the direction of avoidance. Research into the influence of reward on frontal asymmetry supports this connection (Miller and Tomarken, 2001; Pizzagalli et al., 2005) and higher levels of left frontal activation have been associated with trait measures of behavioural activation (Coan and Allen, 2004; Harmon-Jones and Allen, 1997). The relationship between motivational direction and affective valence encapsulated by frontal EEG asymmetry is implicit within a performance setting.

This paper will focus on the use of psychophysiological measurement to capture states of user engagement and how these data may be used to facilitate real-time system adaptation. With respect to the first aspect, two experiments designed to measure task engagement using psychophysiological measures of EEG activity (frontal theta and frontal asymmetry) and the cardiovascular response (SBP) are described in the following sections. The aim of the first experiment was to manipulate engagement via performance feedback, i.e. one group of participants were exposed to false performance feedback of progressive success whereas another group received feedback of cumulative failure. The second experiment employed a design where engagement was simultaneously manipulated by task difficulty (i.e. easy, hard and impossible) and the presence of financial rewards.

2 Experiment one: manipulation of task engagement via performance feedback

2.1 Description of study

About 34 participants (17 males and 17 females) formed two independent groups. A positive feedback group completed a working memory task and received false performance scores indicating a gradual improvement in performance overtime. A negative feedback group completed the same task but received scores indicating a gradual decline in performance.

The memory task was computer based and developed from the '*n*-back task' as used by Gevins et al. (1998). The version of the task used in this study was a two back task where participants continuously compared a currently presented stimulus to one seen two trials previously. Participants were presented with a 3 × 3 grid. On each trial, a green square appeared at one of the nine grid locations for 1.75 sec and was immediately followed by the next square. Participants were asked to respond on every trial by pressing one of two keyboard buttons to indicate that the location of the current square was either in the same location as the square seen two trials before (a match) or in a different location (a mismatch). The task was divided into five blocks, each of which contained 90 trials. Each block lasted just over 2.5 min and matches occurred on approximately 35% of trials. In the experimental session of the study, participants were provided with false performance feedback as a percentage of overall accuracy at the end of each task block.

Performance feedback was presented visually via a second computer placed adjacent to the memory task computer. Participants were led to believe that performance data were being calculated in real time by this second computer following each block of task activity. This illusion was achieved via a macro written in Microsoft Excel. The macro simulated a process of calculation and analysis and produced a chart to display performance accuracy. Each chart also included performance levels from any previous block/s which provided a visual representation of a gradual decline in performance for the negative feedback group and a gradual improvement in performance for the positive feedback group. Both groups received performance feedback of 60% after block 1 and both groups showed a cumulative decline or increase of 11% in total from block 1 to 5. For the negative feedback group, performance accuracy scores fell from 60% after block 1 to 56% after block 2, to 53% after block 3, to 52% after block 4 and finally reached 49% after block 5.

Blood pressure was recorded using a standard Dinamap apparatus with the pressure cuff placed over the brachial region of the participant's left arm. Initial screen and baseline readings were taken at the start of the experiment. Whilst participants worked on the memory task, two blood pressure readings were taken. EEG was recorded using 32 active electrodes and sampled at 512 Hz via a BioSemi system. Offline, EEG signals were corrected for ocular and physical artefacts and filtered using high and low band pass filters of 0.16 Hz and 15 Hz, respectively. Artefact free epochs were then analysed via fast Fourier transform which yielded mean power in the alpha (8–12 Hz) bandwidth. Alpha activity in the right hemisphere relative to homologous left hemisphere sites was calculated (ln [right] – ln [left]) (Allen et al., 2004) to produce scores of alpha asymmetry for the following pairs of frontal sites: Fp2–1, Af4–3, F4–F3, FC2–FC1 and FC6–FC5. Theta activity was collected from frontal, central areas (Fz). Facial electromyographic activity (fEMG) was recorded to attain measures of muscle activity for the corrugator supercilii, which has been linked to the experience of negative affect (Larsen et al., 2003).

The procedure for the experiment and data collection protocols were approved by the University Research Ethics Committee prior to commencement of the experiment.

2.2 Results of experiment one

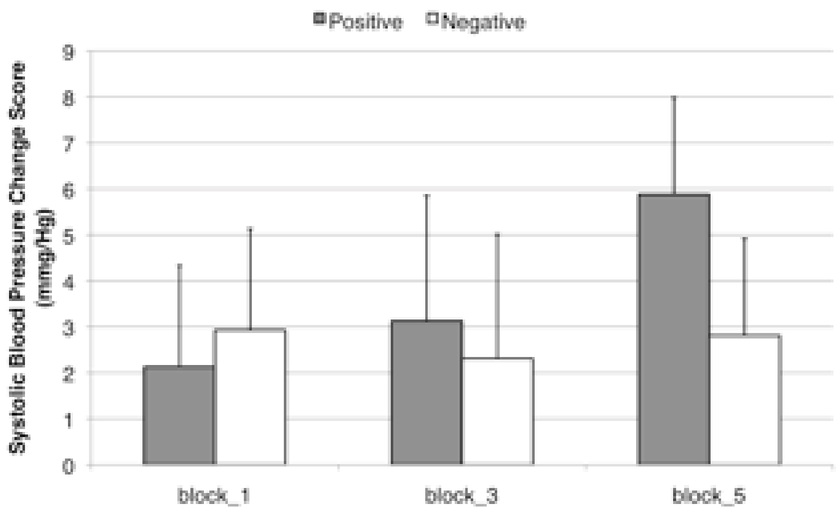
2.2.1 EEG data

Two participants were excluded from this analysis due to technical problems with the data collection (one from each feedback group). The MANOVA analysis of EEG data revealed significant main effects for frontal asymmetry site, $F(4, 26) = 5.70$, $p < 0.01$ and experimental condition, $F(1, 29) = 4.05$, $p < 0.05$. The effect of experimental condition for EEG frontal asymmetry demonstrated that frontal asymmetry score (across all sites) was significant higher in the presence of performance feedback, i.e. higher level of activation in left hemispheric sites during feedback condition. There was no effect of feedback on levels of frontal theta activity.

2.2.2 Systolic blood pressure

The ANOVA model conducted on SBP data revealed a significant main effect for experimental condition, $F(1, 30) = 4.82$, $p < 0.05$, i.e. SBP was significantly higher during Feedback [$M = 115.78$] compared to the No feedback condition [$M = 112.71$]. The same model also revealed significant interactions between Feedback group × Task block, $F(4, 27) = 3.55$, $p < 0.05$, and Feedback group × Experimental condition × Task block, $F(4, 27) = 3.20$, $p < 0.05$. For the positive feedback group, mean SBP was significantly higher at Task block 5, $t(15) = 3.26$, during the Feedback condition compared to the No feedback condition (Figure 1).

Figure 1 Mean SBP (mm Hg^{-1}) for positive feedback group compared across both experimental conditions ($N = 16$)



2.2.3 Corrugator activity

The corrugator data were subjected to ANOVA model with an eyes open baseline included as an additional cell in the task block factor. This analysis revealed no significant effects. The trend of the data was to increase in presence of feedback and this trend was particularly prominent during task block 5.

3 Experiment two: manipulation of task engagement via cognitive demand and financial reward

3.1 Description of experiment

About 20 participants (10 male and 10 female) took part in the research. Participants had a mean age of 24.25 years (SD 4.13). Cognitive effort was elicited with a continuous matching verbal working memory task known as the *n*-back task. This task requires participants to indicate if the currently presented stimulus matches one shown on an earlier occasion. Blocks were one of three possible memory load levels. Participants were required to indicate for each stimulus if it matched the previous stimulus ('1-back' or low load condition), the stimulus 4-previous ('4-back' or high load condition) and the stimulus 7-previous ('7-back' or excessive load condition). Responses were given with a keyboard press of 1 for match and 2 for non-match, using the right index and middle fingers.

Participants completed each of the three experimental trials under incentive and no-incentive conditions. For the no-incentive condition, participants were told they were taking part in a pilot study for equipment testing and that their data would not be used in the experiment. For the incentive condition, participants were told that for each level they would receive a £5 voucher for good performance, a £10 voucher for very good performance and a £15 voucher for excellent performance (maximum = £45).

ECG activity was measured from BIOPAC electrodes using a lead II configuration (BIOPAC Systems Inc., Goleta, CA), where one electrode was placed on the right shoulder, a ground electrode on the left hip and another electrode on the right hip. Blood pressure measurements were taken using a CARESCAPE Vital Signs Monitor (V100) which involved placement of an inflatable cuff on the upper left arm. Readings of SBP were taken along with diastolic blood pressure, heart rate and mean arterial pressure. A baseline reading was taken during a 3 min period prior to task completion at 90s after the start of this period. Readings were then taken for each experimental trial 60s after onset giving two readings for each condition which were then averaged. Only SBP data were statistically analysed.

Pupil diameter measurements were recorded continuously at a sample rate of 60 Hz with two remote infrared video cameras (Seeing Machines Ltd., Canberra, Australia). The cameras used binocular tracking were mounted on a metal frame 40–50 cm in front of the participant, placed beneath the stimulus display monitor. Pupil size resolution was possible at 0.00001 mm using a 12 mm lens. Data were recorded using FaceLAB 4.6 software. Pupil diameter was measured throughout a 3 min baseline prior to task completion during which participants were required to maintain their gaze at a fixation point (green dot) at the screen centre.

EEG was recorded monopolarly from 64 Ag–AgCl pin-type active electrodes mounted in a BioSemi stretch-lycra head cap. Electrodes were positioned using the 10–20 system and recorded activity from the following sites: frontal pole (FPz, FP1 and FP2), anterior-frontal (AFz, AF3, AF4, AF7 and AF8), frontal (Fz, F1, F2, F3, F4, F5, F6, F7 and F8), fronto-central (FCz, FC1, FC2, FC3, FC4, FC5 and FC6), central (Cz, C1, C2, C3, C4, C5 and C6), temporal (FT7, FT8, T7, T8, TP7 and TP8), parieto-central (CPz, CP1, CP2, CP3, CP4, CP5 and CP6), parietal (Pz, P1, P2, P3, P4, P5, P6, P7, P8, P9 and P10), occipito-parietal (POz, PO3, PO4, PO7 and PO8) and occipital (Oz, O1, O2 ad Iz). The data was visually inspected for artefacts from external electromagnetic sources. Automatic correction of blink artefacts and horizontal and vertical saccades was performed using detection through predefined topographies. Muscle activity over 100 μV was also excluded. Fast Fourier transforms were computed over 50% overlapped windows of 2 sec (512 points). The total power in μV^2 was then obtained for the theta frequency band, which consisted of a 1Hz window taken around the frequency of peak modulation within the 4–7 Hz theta range for each participant. Frontal asymmetry scores were calculated for the alpha bandwidth using the following metric: Ln [right total alpha power] – Ln [left total alpha power] (Coan and Allen, 2003). Asymmetries were also calculated for homologous electrode pairs AF4–AF3, F2–F1, FC2–FC1 and C2–C1. Positive values on the index indicated greater relative right alpha power and greater relative left frontal activity, while greater relative right frontal activity was indicated by negative values.

3.2 Results of experiment two

A repeated measures ANOVA on accuracy scores revealed omnibus effects for load [$F(2, 18) = 153.2$, $p < 0.001$] and incentive [$F(1, 19) = 7.71$, $p < 0.05$]. *Post hoc* contrasts showed that performance deteriorated from low to excessive load but showed a linear increase with incentive. *Post hoc* tests indicated that performance was increased with an incentive at low [$t(19) = 2.52$, $p = 0.02$] and high [$t(19) = 2.59$, $p = 0.02$] loads, but not at excessive load.

An incentive *x* load repeated measures ANOVA was performed on SBP data. Main effects were present for incentive [$F(1, 19) = 25.25$, $p < 0.001$] and load [$F(2, 18) = 4.4$, $p < 0.05$]. *Post hoc t*-tests revealed SBP increased with incentive in all load conditions, with the largest effect at high loads. *T*-tests were also conducted between task loads for each incentive condition to detect load effects. The results showed SBP dropped from high to excessive load in the incentive [$t(19) = 2.5$, $p = 0.021$] and no incentive [$t(19) = 2.6$, $p = 0.003$] conditions. This effect is illustrated in Figure 2.

A repeated measures incentive *x* load ANOVA conducted on the heart rate data revealed a main effect for incentive [$F(1, 19) = 9.07$, $p < 0.01$] but not for load. *Post hoc t*-tests found heart rate was significantly higher with an incentive than without an incentive at high task loads [$t(19) = 2.46$, $p = 0.024$]. No significant main effects for load or incentive were found during the analysis of either respiration or pupillometry data.

A three-way repeated measures ANOVA with factors of electrode site (3: AFz, Fz, FCz), incentive (2: no incentive, incentive) and load (3: low, high, excessive) were performed on theta power values (in 1 Hz window around peak frequency). Main effects were present for load [$F(2, 16) = 3.52$, $p = 0.05$] and electrode site [$F(2, 16) = 47.31$, $p < 0.001$]. A load *x* site interaction was also found [$F(4, 14) = 4.3$, $p < 0.05$]. *Post hoc* contrasts revealed a quadratic trend for load [$F(1, 17) = 7.41$, $p < 0.05$] with the greater power at high load. *Post hoc* t-tests showed that the effect for load was related primarily to a decrease in theta power at excessive load compared to high loads in the incentive condition at Fz: [$t(17) = 2.98$, $p = 0.008$] and AFz: [$t(17) = 2.6$, $p = 0.019$]. Also in the incentive condition at AFz theta increased from low to high load: [$t(17) = -2.85$, $p = 0.011$] (see Figure 3).

Figure 2 Mean and SD SBP readings for low, high and excessive loads with and without an incentive in mmHg ($N = 20$)

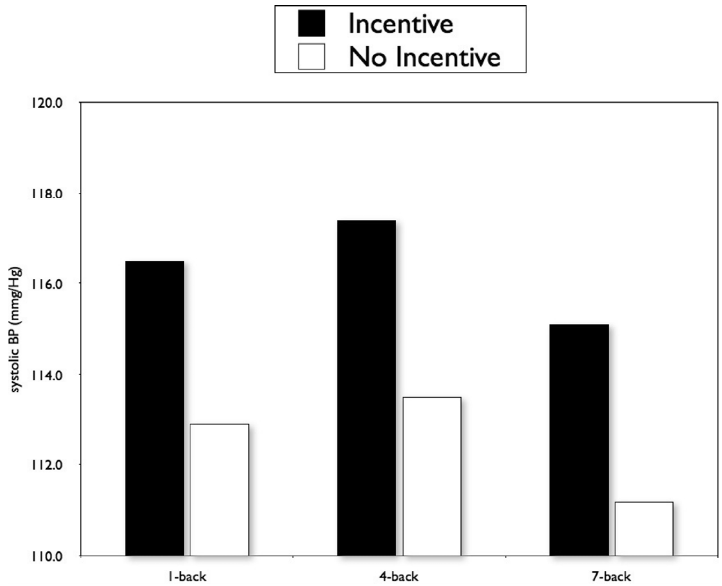
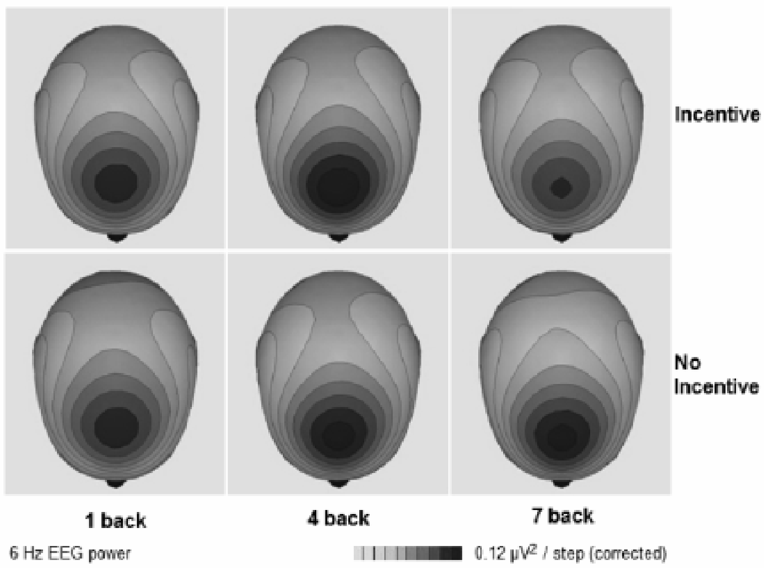


Figure 3 Grand average ($N = 18$) topographic distribution of spectral power at 6 Hz for low, high and excessive loads with and without an incentive



EEG frontal asymmetry measures were taken from the following pairs of electrodes: AF4–AF3, F2–F1, FC2–FC1 and C2–C1. Electrode sites were chosen on the basis of previous robust asymmetry findings at frontal and anterior-frontal sites. Asymmetry metrics were calculated using total power in the conventional 7.5–13 Hz alpha band. An incentive *x* load *x* site repeated measures ANOVA revealed a main effect for load [$F(2, 16) = 4.56$, $p < 0.05$] and site, [$F(3, 15) = 3.73$, $p < 0.05$] and interactions between incentive and load [$F(2, 16) = 6.01$, $p < 0.05$] and incentive, load and site [$F(3.049, 51.84) = 5.3$, $p < 0.005$]. The results showed greater relative left activation with an incentive under the high load condition, however, incentive effects were not discernible at low and excessive loads. *T*-tests were also conducted for low vs. high and high vs. excessive loads for each incentive condition at AF4–AF3. Results revealed a stepwise decrease in asymmetry from low to high load [$t(17) = 3.244$, $p = 0.005$] and high to excessive load [$t(17) = 3.1$, $p < 0.01$] in the no incentive condition, though no load effects could be found in the incentive condition.

AU: Kindly check the sentence ‘An incentive *x* load *x* site…’ seems to be incomplete.

4 Explanation of findings

Two experiments were conducted to identify the sensitivity of psychophysiological variables to the manipulation of task engagement. The first experiment attempted to manipulate task engagement in two ways. First, it was anticipated that performance feedback inevitably increases task engagement as the quality of one’s own performance is rendered more salient. By providing repeated exposure to both positive and negative feedback, we anticipated different patterns of mental effort investment; specifically, positive feedback should reduce effort investment (as participants received the impression that performance was consistently improving). It was hypothesised that the presentation of negative feedback would initially mobilise high levels of effort, leading to disengagement towards the latter periods of the task as prompted by repeated exposure to negative feedback. The first hypothesis was supported by the frontal asymmetry data; participants exhibited higher left frontal activation during the feedback condition (regardless of whether feedback was positive or negative). The only psychophysiological response to the direction of feedback was found with respect to SBP (Figure 1). This variable is associated with sympathetic activation of the autonomic nervous system, i.e. increased activation. This pattern was unexpected but was interpreted in the following way; contrary to expectations, positive feedback increased participants’ appraisal of their own capability, which motivated these individual to both aspire towards higher levels of performance and increase mental effort mobilisation. The absence of the opposite trend in the presence of negative feedback was puzzling; perhaps negative feedback had no impact on any psychophysiological indicators of effort because the task was quite abstract and there were no negative consequences of task failure.

The second study manipulated two potential sources of mental effort investment, task demand and financial incentives. It was anticipated that task demand would influence effort investment in a quadratic trend as predicted by the motivational intensity model (Wright and Kirby, 2001), i.e. the 1-back (1b) and 7-back (7b) would both reduce effort due to lack of challenge and excessive demand, respectively. The purpose of the incentive manipulation was to increase effort by reinforcing the level of goal commitment of the individual (Locke and Latham, 1990), i.e. by providing financial consequences for good or bad performance. However, it was predicted that the presence of financial incentives would only increase effort investment when good performance was achievable. In this case, we expected to see an interaction between demand and incentive in the 1b and 4-back (4b) conditions but not for the 7b task where good performance was unachievable. The analysis of performance demonstrated an anticipated decline as task demand increased. The presence of financial incentives improved participants' performance but only on the 1b and 4b tasks where good performance was attainable.

Psychophysiological data were collected from several sources: pupilometry, the cardiovascular system and the EEG. Systolic BP responded to both task demand and incentive manipulations as expected – demonstrating a quadratic trend for task analysis (increasing from the 1b to the 4b then declining during the 7b) and increasing in the presence of financial reward (Figure 2). It was significant that reward made maximal impact on SBP during the 4b condition when task demand reached maximum challenge. The analysis of heart rate revealed an effect for financial reward but not for task load, which may indicate that parasympathetic influences blunted the sensitivity of heart rate to demand. In the case of the ICA (pupilometry), the trend was in the expected direction but the measure was not very sensitive compared to other categories. Frontal theta activity increased in response to demand from the 1b to the 4b condition but consequently declined in the 7b condition (Figure 3). This trend indicated that frontal theta was only augmented in response to working memory load when successful performance was attainable. The frontal EEG asymmetry index was included to capture approach and avoidance motivation in response to task demand and financial incentives. It was anticipated that excessive task demand (7b) would reduce approach motivation whereas the presence of a financial reward would have the opposite effect. Both effects were observed and it was notable that financial reward only augmented approach motivation (frontal left activation) during the 4b condition, i.e. when task demand was challenging but success was attainable. The general picture emerging from this study is that EEG variables were sensitive to cognitive task demand (i.e. increased effort from 1b to 4b condition) and the probability of task success (i.e. reduced effort from 4b to 7b condition). Cardiovascular measures, particularly SBP and heart rate, responded to incentives (as well as task demand in the case of SBP).

5 Implications for system design

The experimental work demonstrates that it is possible to capture correlates of engagement using psychophysiological measures. In the first experiment, increased goal aspiration in response to positive feedback raised SBP, which is an indicator of sympathetic activation. These data suggest that the desire to aim for a higher level of performance represents one source of increased engagement and is associated with an autonomic shift towards sympathetic activation. The second study manipulated engagement in two ways, by manipulating cognitive load and the motivational significance of the task (via financial reward). The results demonstrated that the cognitive dimension of engagement was captured via EEG markers such as augmented frontal theta. The presence of financial incentives tended to influence cardiovascular measures, such as heart rate, whilst SBP was equally sensitive to both categories of engagement manipulation. These findings indicate that different sources of engagement, such as cognitive challenge and motivational significance, may be discriminated by psychophysiological markers. With respect to experiment two, it should be noted that both frontal theta and SBP declined when demand was excessive (as illustrated in Figures 2 and 3). This trend demonstrated the possibility of using psychophysiological markers of task engagement to identify the 'tipping point' where highly demanding performance (indicative of a flow state/high engagement) may shift into an undesirable state of disengagement.

These experimental results suggest that task engagement may be captured using real-time psychophysiology, but if this is the case, how may tapping this dimension in real-time enable adaptive strategies to improve HCI in the context of a computer game? Adaptive game dynamics can be characterised as either facilitating a transition towards a desirable state or away from an undesirable one. Three categories of adaptive gameplay mechanic have been proposed with reference to PC (Gilleade et al., 2005).

1 *'Assist-me'*: game adapts play to alleviate the player's level of frustration (i.e. away from frustration).

2 *'Challenge-me'*: game adapts play to optimise the level of challenge (i.e. towards a state of flow).

3 *'Emote-me'*: game adapts play to elicit a prescribed emotional response (e.g. towards an emotion relevant to the experience of the game narrative).

The 'assist-me' game mechanic is aimed at the more casual player who is considered to have a lower tolerance for frustration relative to the more experienced or 'hardcore' player. As such these causal players are more likely to transition into an undesirable state more readily than the experienced category of player. It has been demonstrated that aiding players in order to cope with frustration during an adventure game extended game involvement relative to those players who did not receive help (Klein et al., 2002). However, the specific category of adaptation employed by the system depends on the cause of frustration. In Gilleade et al. (2005), frustration during play was contextualised as being either 'at-game' – characterised as a failure to interact with the game (e.g. failed to press a button on time) or 'in-game' – characterised as a failure to interact within the game (e.g. becoming lost in the game world). The discrimination of different categories of frustration would be clarified by monitoring the performance of the player or the game state in conjunction with psychophysiology in order to target the type of help provided by the system. Psychophysiological measures are very sensitive but require data from additional sources to provide the necessary context to select a specific type or category of help (Fairclough, 2009).

'Challenge-me' gameplay adaptations aim to maintain the optimum level of engagement in the player. Traditionally, games provide only a prescribed set of game challenges (e.g. easy, medium and hard). Adaptive games can modify the challenge in accordance with

1 the player's game performance

2 their psychophysiological state

3 a combination of the two, i.e. a multimodal representation of the user (Kapoor et al., 2007; Pantic and Rothkrantz, 2003).

A particular challenge for realising 'challenge-me' adaptation is how to determine an optimum level of challenge for the individual player, i.e. one that increases or sustains engagement without tipping the player into disengagement. The most straightforward solution to this problem would be to provide the player with many options to configure the gaming experience (e.g. AI difficulty and game speed), however this would unnecessarily complicate the game set up. A more elegant solution was to allow the player to select the emotional characteristics of the gaming experience using an 'emotion knob' encapsulating all the configuration options within the emotional experience to be elicited (Saari and Ravaja, 2005).

The structure of contemporary computer games is for the player to overcome a static series of challenges presented in linear order of increasing difficulty. In addition, the player can select the range of task difficulty (lowest to highest level of challenge) as a skill setting before the game begins. Recent research has emphasised the importance of autonomy and competence for players of computer games (Ryan et al., 2006). The intrinsic motivation for players (i.e. willingness to play the game) is related to the provision for choice and freedom within the game, as well as the need for challenge and to opportunity to acquire new skills. The question then arises: Does the introduction of a biocybernetic loop within a PC, which 'manages' the HCI according to preconceived meta-goals (to challenge, to help, etc.), represent a threat to the autonomy and competence of the player? A game designed to manipulate task demand to consistently engage runs a risk of disempowering the player by preventing excessive exposure to either success or failure. This potential problem stems from over-corrective activation of the loop, and therefore, it may be prudent to design the biocybernetic loop to respond conservatively and subtly within gaming applications. It is important that the loop does not anticipate or constrain the player to an excessive degree.

The biocybernetic loop may use two inherent dynamics: negative or positive feedback control. This is another important design option for PC. Negative control loops create stability by reducing the discrepancy between the input signal (real-time psychophysiological measure of engagement) and a desired standard (the desired level of engagement). Negative feedback control is perfect if the system has been designed to keep the user within a 'safe' zone, such as avoiding extremes of fatigue or stress. By contrast, positive feedback control is designed to amplify the discrepancy between the input signal and the desired standard in an exponential fashion. Positive feedback control leads to performance instability (Freeman et al., 1999); a biocybernetic system working on this basis would adjust the desired standard of engagement upwards as the person became more engrossed with the task. In the case of safety systems, such as adaptive automation, it is desirable to keep the operator within a stable zone that optimises the effectiveness of performance. However, this kind of stability is an anathema to the computer gamer who is motivated by new challenges and personal autonomy (Ryan et al., 2006). It is argued that one technique to preserve the motivation of the gamer is to use positive feedback control in order to 'push' performance to a higher level. It may be possible to base biocybernetic control of the game on a positive control dynamic in its entirety, but this may be prove to be exhausting for the player (and hence may be detrimental to health). For sustained game play, it is envisaged that intervals of stability achieved via negative control will be interspersed with unstable episodes courtesy of a positive control dynamic. In this way, the player is 'stretched' and then granted an opportunity to consolidate his or her new skills. Alternatively, this strategy of alternation or cycling between negative and positive control represents an attempt to fulfil both meta-goals simultaneously, i.e. to use positive control to provoke intense engagement and negative control to assuage any resulting accumulation of stress and/or fatigue.

To conclude: PC has enormous potential to innovate real-time software adaptation by providing context of the user state. The experiments in this paper demonstrated how EEG and cardiovascular markers of engagement may respond to different factors associated with cognition and emotion. These psychophysiological markers could provide the raw input required to drive software adaptation that challenges and aids the user in a timely, intuitive and dynamic fashion.

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References

Allanson, J. (2002) 'Electrophysiologically interactive computer systems', *IEEE Magazine*, Vol. 35, March, pp.60–65.

Allanson, J. and Fairclough, S.H. (2004) 'A research agenda for physiological computing', *Interacting with Computers*, Vol. 16, pp.857–878.

Allen, J.J.B., Coan, J.A. and Nazarian, M. (2004) 'Issues and assumptions on the road from raw signals to metrics of frontal EEG asymmetry in emotion', *Biological Psychology*, Vol. 67, pp.183–218.

Allison, B.Z., Wolpaw, E.W. and Wolpaw, J.R. (2007) Brain–computer interface systems: progress and prospects', *Expert Review of Medical Devices*, Vol. 4, No. 4, pp.463–474.

Beatty, J. (1982) 'Task-evoked pupillary responses, processing load and the structure of processing resources', *Psychological Bulletin*, Vol. 91, No. 2, pp.276–292.

Burleson, W. and 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*.

Chanel, G.C. and Rebetez, C. (2008) 'Boredom, engagement and anxiety as indicators for adaptation to difficulty in games', Paper presented at the *12th International Conference on Entertainment and Media in the Ubiquitous Era*.

Chen, J. (2007) 'Flow in games (and everything else)', *Communications of the ACM*, Vol. 50, No. 4, pp.31–34.

Coan, J.A. and Allen, J.J.B. (2003) 'Frontal EEG asymmetry and the behavioural activation and inhibition systems', *Psychophysiology*, Vol. 40, pp.106–114.

Coan, J.A. and Allen, J.J.B. (2004) 'Frontal EEG asymmetry as a moderator and mediator of emotion', *Biological Psychology*, Vol. 67, pp.7–49.

Csikszentmihalyi, M. (1990) *Flow: The Psychology of Optimal Experience*. New York: Harper Perennial.

Davidson, R.J. (2004) 'What does the prefrontal cortex "do" in affect: perspectives on frontal EEG asymmetry research', *Biological Psychology*, Vol. 67, pp.219–233.

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*, Vol. 21, pp.133–145.

Freeman, F.G., Mikulka, P.J., Prinzel, L.J. and Scerbo, M.W. (1999) 'Evaluation of an adaptive automation system using three EEG indices with a visual tracking task', *Biological Psychology*, Vol. 50, pp.61–76.

Gaillard, A.W.K. (2001) 'Stress, workload, and fatigue as three biobehavioural states: a general overview', in P.A. Hancock and P.A. Desmond (Eds.), *Stress, Workload, and Fatigue*. Mahweh, NJ: Erlbaum, pp.623–639.

Gevins, A. and Smith, M.E. (2003) 'Neurophysiological measures of cognitive workload during human–computer interaction', *Theoretical Issues in Ergonomic Science*, Vol. 4, Nos. 1–2, pp.113–121.

Gevins, A., et al. (1998) 'Monitoring working memory load during computer-based tasks with EEG pattern recognition models', *Human Factors*, Vol. 40, No. 1, pp.79–91.

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

Harmon-Jones, E. and Allen, J.J.B. (1997) 'Behavioural activation sensitivity and resting frontal EEG asymmetry: covariation of putative indicators related to risk for mood disorders', *Journal of Abnormal Psychology*, Vol. 106, No. 1, pp.159–163.

Kapoor, A., Burleson, W. and Picard, R.W. (2007) 'Automatic prediction of frustration', *Int. J. Human–Computer Studies*, Vol. 65, pp.724–736.

Klein, J., Moon, Y. and Picard, R.W. (2002) 'This computer responds to user frustration: theory, design and results', *Interacting with Computers*, Vol. 14, pp.119–140.

Larsen, J.T., Norris, C.J. and Cacioppo, J.T. (2003) 'Effects of positive and negative affect on electromyographic activity over the zygomaticus major and corrugator supercilii', *Psychophysiology*, Vol. 40, pp.776–785.

Locke, E.A. and Latham, G.P. (1990) *A Theory of Goal Setting and Task Performance*. Englewood Cliffs, NJ: Prentice-Hall.

Marshall, S.P., Davis, C.L. and Knust, S.R. (2004) *The Index of Cognitive Activity: Estimating Cognitive Effort from Pupil Dilation*. San Diego, CA: EyeTracking Inc.

Matthews, G., et al. (2002) 'Fundamental dimensions of subjective state in performance settings: task engagement, distress and worry', *Emotion*, Vol. 2, No. 4, pp.315–340.

Miller, A. and Tomarken, A.J. (2001) 'Task-dependent changes in frontal brain asymmetry: effects of incentive cues, outcome expectancies and motor responses', *Psychophysiology*, Vol. 38, pp.500–511.

Mulder, G. (1986) 'The concept and measurement of mental effort', in G.R.J. Hockey, A.W.K. Gaillard and M.G.H. Coles (Eds.), *Energetical Issues in Research on Human Information Processing*. Dordrecht, The Netherlands: Martinus Nijhoff, pp.175–198.

Nacke, L. and Lindley, C.A. (2008) 'Flow and immersion in first-person shooters: measuring the player's gameplay experience', Paper presented at the *Conference on Future Play: Research, Play, Share*.

Pantic, M. and Rothkrantz, L.J.M. (2003) 'Towards an affect-sensitive multimodal human–computer interaction', *Proceedings of the IEEE*, Vol. 91, No. 9, pp.1370–1390.

Picard, R.W., Vyzas, E. and Healey, J. (2001) 'Towards machine emotional intelligence: analysis of affective physiological state', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 10, pp.1175–1191.

Pizzagalli, D., Sherwood, R.J., Henriques, J.B. and Davidson, R.J. (2005) 'Frontal brain asymmetry and reward responsiveness', *Psychological Science*, Vol. 16, No. 10, pp.805–813.

Pope, A.T., Bogart, E.H. and Bartolome, D.S. (1995) 'Biocybernetic system evaluates indices of operator engagement in automated task', *Biological Psychology*, Vol. 40, pp.187–195.

Richter, M., Friedrich, A. and Gendolla, G.H. (2008) 'Task difficulty effects on cardiac activity', *Psychophysiology*, Vol. 45, pp.869–875.

Richter, M. and Gendolla, G.H.E. (2007) 'Incentive value, unclear task difficulty, and cardiovascular reactivity in active coping', *Int. J. Psychophysiology*, Vol. 63, No. 3, pp.294–301.

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

Saari, T. and Ravaja, N. (2005) 'Towards emotionally adapted games based on user controlled emotion knobs', Paper presented at the *DiGRA 2005: Changing Views: Worlds in Play*.

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

Wilson, G.F. and Russell, C.A. (2007) 'Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding', *Human Factors*, Vol. 49, No. 6, pp.1005–1018.

Wright, R.A. (2008) 'Refining the prediction of effort: Brehm's distinction between potential motivation and motivation intensity', *Social and Personality Psychology Compass*, Vol. 2, No. 2, pp.682–701.

Wright, R.A. and Kirby, L.D. (2001) 'Effort determination of cardiovascular response: an integrative analysis with applications in social psychology', in M.P. Zanna (Ed.), *Advances in Social Psychology*. San Diego, CA: Academic Press. pp.255–307.