Psychophysiological Inference and Physiological Computer Games

Stephen H Fairclough

Liverpool John Moores University,
School of Psychology
Webster Street, Liverpool, L2 3ET, UK

s.fairclough@ljmu.ac.uk

ABSTRACT

This paper is concerned with the use of real-time psychophysiological monitoring to control the interaction between the player and the computer game. In the context of the current paper, psychophysiology is used to represent the cognitive/motivational/emotional state of the player. The paper explores fundamental concepts and assumptions underpinning the design of a physiological computer game, including: (1) the use of psycho-physiological inference, (2) the representation of the state of the player, and (3) the biocybernetic control loop.

Categories and Subject Descriptors

H1.2 [**User/Machine Systems**]: Human Factors. H5.2 [**Information Interfaces and Presentation**]: User Interfaces. I.2 [**Artificial Intelligence**]: Games.

General Terms

Algorithms, Measurement, Human Factors.

Keywords

Games, Affective Computing, Psychophysiology.

1. INTRODUCTION

Physiological Computing [1] represents a category of affective computing [2] that incorporates real-time software adaptation to the psychophysiological activity of the user. The goal of this approach is to devise a computer system that responds in a rational and strategic fashion to real-time changes in user emotion (e.g. frustration), cognition (e.g. attention) and motivation as represented by psychophysiology. At present, human-computer interaction is both explicit (via keyboard or mouse) and asymmetrical (i.e. the computer can convey a wealth of information regarding its status to the user whereas the user is able to convey very little to the computer about his or her status) [3]. The central innovation of the physiological computing approach is to enable implicit and symmetrical human-computer communication by granting the software access to a representation of the user's psychological status.

Research into physiological computing has been directed towards a number of technological domains, such as: cockpit automation [4, 5], computer-based learning [6], and robotics [7]. The application of this approach to computer games remains relatively overlooked with a small number of exceptions [8, 9]. The incorporation of psychophysiology into gaming software has the potential to tailor the gaming experience to the cognitive, motivational and emotional responses of the player in real-time. This is important innovation as gaming software is designed to reliably create a positive state of psychological challenge. In addition, game designers place great emphasis on players' emotional engagement with the computer game [10] in order to expand player demographics, and to achieve higher levels of immersion within the game 'world'. Physiological computing offers the opportunity for real-time adaptation of gaming parameters to promote positive experience and to avoid undesirable responses such as frustration or boredom.

The physiological computing approach has the potential to revolutionize the game industry, in terms of hardware and software design, as well as rewriting the modes of information flow within the human-computer interaction. However, the potential of physiological computer games will only be fully realised by paying close attention to the scientific foundations of this technology, and a clear appreciation of how closed-loop systems function within this context.

2. PSYCHOPHYSIOLOGICAL INFERENCE

In principle, there are several possible methods to represent the psychological state of the user to a computerized monitor. Automatic detection of facial expression may be achieved at a reasonable level of accuracy via machine vision algorithms for core emotional expression [11]. Similarly, detection of vocal affect offers another option for data collection, particularly for those systems that rely on speech as the primary mode of user input [12]. A straightforward approach is to monitor the behavioural response from the user by measuring physical force when manipulating input devices to index frustration[13]. Psychophysiological indices offer several advantages over these methods [14]. Psychophysiological changes are continuous whereas vocal and behavioural expressions are discrete and episodic. Psychophysiological measures are covert and implicit whereas facial expression relies to an extent on the display rules governing emotional expression in the public domain. Psychophysiology can be also used to operationalise psychological variables beyond the emotional domain, such as cognition (attention, cortical activation) and motivation (mental effort). Finally, psychophysiological activity represents the only available data source when the user interacts with the computer without any explicit communication (emotional display or speech) or the operation of an input device. The primary disadvantages of psychophysiology is that data capture with current technology is often intrusive, although there is a limitation of non-ambulatory apparatus, which is currently the standard in this field [15, 16].

The complexity of psychophysiological inference [17, 18] is a fundamental issue for the development of physiological computing. These systems rely upon a tacit assumption that the psychophysiological measure (or array of measures) is an accurate one-to-one representation of a relevant psychological dimension, e.g. mental effort, task engagement, frustration. This assumption of isomorphism is often problematic as the relationship between physiology and psychology is complex and may be described as [17, 18] :

- Many-to-one (i.e. two or more physiological variables may be associated with the relevant psychological element)
- One-to-many (i.e. a physiological variable may be sensitive to one or more psychological elements)
- Many-to-many (i.e. several physiological variables may be associated with several psychological elements)

In the many-to-one case, an investment of mental effort in response to a demanding task may be only be fully represented by changes in cortical activity from the frontal lobes [19], increased systolic blood pressure [20] and changes in heart rate variability [21]. This pattern of linkage is reversed in the one-to-many relationship; for example, systolic blood pressure may increase when a person is excited, frustrated or stressed [22]. In the many-to-many case, a mixture of increased mental effort and stress may combine to exert a multiple, overlapping paths of influence over both systolic blood pressure and heart rate variability.

The implications of this analysis for the development of physiological computing should be clear. At a basic level, any system that operationalises a psychological element using a psychophysiological inference that falls into the one-to-many or many-to-many categories may not respond as anticipated by the user or the designer. This is mainly because the linkage between physiology and psychology is not 'clean,' and the variable is responding to other psychological elements besides the desired one. For example, imagine a game designed to reduce player anger or frustration that uses systolic blood pressure to infer frustration levels, and reduces the demands of the game as a response. Frustration or anger does increase blood pressure [23], but increased systolic blood pressure also characterizes a state of positive challenge [24], e.g. a one-to-many relationship. Therefore, the system may inadvertently reduce game demand when the player is in a state of positive challenge, which would frustrate the player, leading to increased blood pressure, which prompts a second downward adjustment of demand from the software and so on. The fidelity of the psychophysiological inference is vital for a physiological game to respond in an appropriate fashion.

The selection of 'strong' psychophysiological candidates for a physiological computing system requires that candidate variables have demonstrated a degree of validity. At a basic level, the careful selection of psychophysiological variables based on a thorough review of the existing literature will ensure a requisite degree *content validity*, i.e. that a precedent exists (either theoretically or experimentally) for the variables to measure what the designer intends to measure. However, the designer may also wish to test the quality of the psychophysiological inference experimentally to establish a degree of *concurrent validity*, i.e. how well does the psychophysiological measure predicts an psychological outcome based upon another set of variables? Several approaches have been adopted to establish the concurrent validity of psychophysiological measures by inducing emotional states in the laboratory, these include: face-pulling [25], exposure to emotional media [26, 27] and exposure to demanding or frustrating tasks [28, 29]. In most cases, concurrent validity is demonstrated by correlating psychophysiological data with self-report data or using discriminant analyses to distinguish different patterns of psychophysiological activity. The systematic approach associated with concurrent validity is contrasted with the concept of face *validity*, which captures a looser, 'quick-and-dirty' approach where the quality of the psychophysiological inference is assessed based on intuition or direct experience.

In the interests of optimising the quality of psychophysiological inference, which is the cornerstone of the physiological computing system, it is important to opt for concurrent validity over face validity. However, this approach introduces a number of methodological complexities. As psychophysiological variables seek to represent private psychological events, subjective self-reports represent an important psychological outcome with which to 'benchmark' the psychophysiological response. This link between physiology and self-report is often problematic as the latter are totally reliant on conscious perception, prone to bias due to personality or memory distortion [30], and therefore, their correspondence with psychophysiological activity is often erratic [31]. For example, in a study conducted in our laboratory, the maximum amount of variance associated with a subjective index of task engagement captured by an array of psychophysiological variables never exceeded 53% across the whole group [28]. If physiological computing systems are to be developed on the basis of concurrent validity, the sensitivity of psychophysiology should be tied to alternative outcomes in addition to subjective self-report, such as: implicit observable behaviours (facial expression, verbal gestures), performance quality (rate of progress through goals, frequency of errors) and measures of motivation (e.g. goal setting, desire to continue playing the game). It is proposed that the simultaneous consideration of multiple outcomes provides the strongest evidence for concurrent validity.

It is reasonable that a designer or scientist should view the criteria of face validity as a poor relation to content and criterion validity. However, consider the different varieties of validity from the perspective of the player engaged with a physiological computer game. If the player experiences an adverse subjective state, such as frustration, he or she expects the software to respond accordingly, by making the task easier or offering help. In other words, the player assesses the system response *purely* based on subjective self-assessment, which represents a form of face validity. Human factors research into the use of psychophysiology to control adaptive automation has included both approaches. The work conducted by NASA [4] used a generic measure of cortical activation via EEG to capture task engagement. In another study, a psychophysiological algorithm was generated individually for each participant in order to produce a personalised, operationalisation of subjective mental effort [32]. The latter study provided no evidence for the superiority of personalised approach (which emphasized face validity) over the generic approach (which emphasized content validity). From a usability perspective, the personalised approach offers the advantage of tailoring the psychophysiological inference to the individual– however in doing so, runs the risk of 'blunting' the sensitivity of psychophysiological variables, which respond to both conscious and unconscious activity at the psychological level. Designers of physiological computer games should consider both forms of validity when assessing the psychophysiological inference used by their systems.

Physiological computer games require strong psychophysiological inference to produce accurate and timely interventions. This is particularly important as the system must measure and diagnose in real-time. The linkage between physiological variables and psychological elements must be sensitive, discriminative and based on existing research. The quality of the psychophysiological inference should be tested with respect to both concurrent validity (in the interests of basic research) and face validity (in the interests of system usability). At the present time, there is little research contrasting generic psychophysiological algorithms with those generated specifically for the individual. Dynamic computer algorithms such as neural networks and evolutionary algorithms may offer a solution that satisfies both criteria of concurrent and face validity [33, 34].

3. REPRESENTATION OF THE PLAYER

If the psychophysiological inference fulfills the criteria of validity, the designer may consider how they wish to represent the psychological status of the player to the system. This is an important aspect of system design that determines the range of adaptive strategies available to physiological computer game as well as the "intelligence" exhibited by the system.

Physiological computing systems all contain an element that may be termed an adaptive controller. This element represents the decision-making process underlying software adaptation. In its simplest form, these decision-making rules may be expressed as simple Boolean statements; for example, IF frustration is detected THEN reduce game demand. The adaptive controller encompasses not only the decision-making rules, but also the psychophysiological inference that is implicit in the quantification of those trigger points used to activate the rules. In our study [32], for example, the adaptive controller took the form of a linear equation to represent the state of the player, e.g. *subjective effort* $= x_1 *$ *respiration rate* $- x_2 *$ *eye blink frequency + intercept*, as well as the quantification of trigger points, e.g. *IF subjective effort* $> y$ *THEN adapt system.* The adaptive controller uses raw psychophysiological input to represent the psychological state of the player to its decision-making rules.

Previous research into physiological computing has represented the psychological state of the user as a one-dimensional continuum, e.g. frustration [8], anxiety [9], subjective effort [32], task engagement [35]. This is an appropriate starting point for research but reliance on a one-dimensional scale restricts the range of options available to of the adaptive controller, which may only characterize the psychological state of the player as low, medium or high on a given dimension. For some systems, where the gaming context is simple and required adaptive range is limited, this may not be a problem. However, the entertainment value of many computer games is based upon an interaction with a complex probabilistic 'world' with many contingencies. These complex game worlds demand an elaborated representation of the player in order to: (1) provide the adaptive controller with a higher fidelity of diagnostic information, and (2) to enable the controller to extend its repertoire of adaptive responses, which, if designed correctly, should have the net effect of enhancing the "intelligence" of the system as a whole.

One straightforward way of moving beyond a one-dimensional representation is model the psychological state of the player in a two-dimensional space. For example, emotion may be decomposed into two dimensions of activation (alert vs. tired) and valence (happy vs. sad) [36]. Within a gaming context, we may wish to consider motivational as well as emotional variables in order to characterize different degrees of challenge. Matthews and colleagues at Dundee University developed a subjective tool called the Dundee Stress State Questionnaire (DSSQ) to assess three meta-factors linked to cognition, motivation and emotion [37]. Two of the DSSQ factors, Task Engagement and Distress, could be used to create a representation of the player interacting with a computer game. Task Engagement was defined as an "effortful striving towards task goals", which increased during a demanding cognitive task and declined when participants performed a sustained and monotonous vigilance task [37]. The Distress meta-factor was characterised by "an overload of processing capacity" which increased when participants experienced a loss of control over performance quality [37]. The combination of engagement and distress allows us to consider the current state of the player as a point in the two-dimensional space shown below.

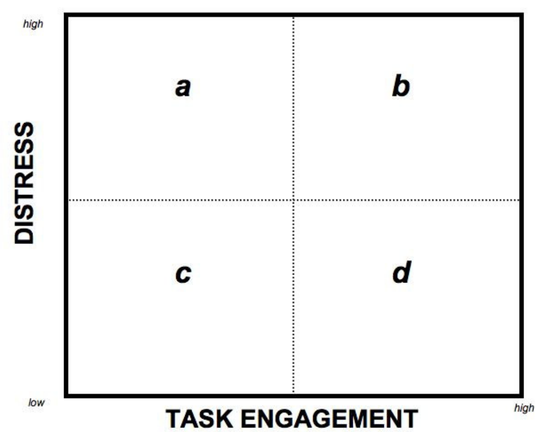

Figure 1. Two-dimensional representation of psychological state of the player.

Figure 1 partitions the psychological state of the player in four quadrants or 'zones'. Zone **a** represents an undesirable state of high distress in combination with low task engagement. In this case, the player is overloaded from a cognitive perspective as well as being disengaged from the task. It might be expected that a player in zone a is on the point of 'giving up' on the game. When engagement and distress are both high (zone **b**), the player occupies a "stretch" zone where they remain highly engaged, but also feel overwhelmed by the task. The player may tolerate this state for a short period, particularly during learning phases of the game. In zone **c**, the player is fundamentally bored as indicated by low levels of distress and engagement. Once again, a player in this zone may choose to switch the game off this state persists for a sustained period. When a player is comfortable with the level of demand yet remains motivated by game play, they fall into zone **d** (low distress and high task engagement). This state may subside into boredom (zone c) if the game lapses into monotony or give way to a learning phase (zone b) if gaming demand increases appropriately. We have attempted to operationalise both dimensions of task engagement and distress using psychophysiological methods during a sustained and demanding task, with some degree of success [28].

The benefit of a two-dimensional player representation should be apparent in the sophistication and timeliness of the response from the adaptive controller. The two-dimensional representation (Figure 1) allows the adaptive controller to make a distinction between two states of low engagement for example, both of which require completely different kinds of adaptive response, e.g. in zone a, task demand ought to be reduced, whereas the opposite response is appropriate in zone c. A complex representation of the player provides the adaptive controller with greater freedom and specificity when selecting an appropriate response.

This approach may be extended by combining the "problem space" of the game with the representation of the player during the formulation of an adaptive response. It is anticipated that representation of the gaming context may greatly enhance the specificity of the adaptive response. An existing model of mental workload [38] may be used for explanatory purposes, which represents the problem space along two dimensions of: (1) distance from the goal, and (2) time remaining to complete the goal. The adaptive response from a physiological computer game may be formulated on the basis of the psychological state of the player (Figure 1) in combination with a representation of the player's position within the problem space of the game, e.g. a second level of two-dimensional space formed by combining distance from the game goal and time remaining to the player.

It is anticipated that early examples of physiological computer games will rely on one-dimensional representations of the player and highly constrained adaptive responses. The full potential of this technology will only be realized when designers incorporate complex representations of the players into their systems – because this complexity is a prerequisite for sophisticated, timely and "intelligent" responses from the game software.

4. THE BIOCYBERNETIC LOOP

The biocybernetic control loop [35] describes the closed loop system that receives psychophysiological data from the player, transforms that data into a computerized response, which then shapes the future psychophysiological response from the player. This is a classic control theory model [39] which may operate on a positive (approach a desirable standard) or negative (avoid an undesirable standard) basis. Control theory models have also been used to study motivation and the process of goal regulation [40], which provides a bridging metaphor between computational and psychological domains.

The biocybernetic control loop at the heart of a physiological computer game is often conceptualized as a negative control loop. Previous research into biocybernetic control demonstrated that negative control loops ensure higher levels of stability [41], which allows the user to avoid undesirable extremes of boredom (zone c in Figure 1) or distress (zone a in Figure 1). This type of biocybernetic control shapes the gaming experience by avoiding those zones associated with sudden transition and instability. However, is a desirable development from the perspective of the player? A positive control loop tends towards instability as player-software loop strives towards a higher standard of desirable performance (zone b in Figure 1). The physiological computer game may wish to incorporate both positive and negative loops into the adaptive controller. During the early stage of game play, a novice player may require 'protection' from overload zones, such as a and b in Figure 1, which is inherent within the negative control loop. However, the 'expert' player may prefer the option of a positive control loop that 'stretches' their skill capacity and directs game play towards high and inherently unstable domains of performance.

The biocybernetic adoption of control theory emphasizes systems which respond to psychophysiology to produce an adaptive response in real-time. In other words, the adaptive response represents a real-time reaction to the present. One problem of this approach is that undesirable psychological states must occur before the biocybernetic control is able to respond. Therefore, it is proposed that biocybernetic systems accumulate psychophysiological data to be used in a predictive sense, i.e. to anticipate and avoid undesirable states. This type of approach calls upon dynamic data modeling such as time series analysis. The goal of this predictive modeling is to enable the biocybernetic loop to respond to the future rather than remaining in the present

Imagine the case of the experienced player who has spent many hours with a physiological computer game. As a novice, the player was aware of how the game software seemed to interact with subjective thoughts and feelings. As the player gained more experience, the adaptive controller was forced to adjust trigger points for interventions and switch between positive and negative modes of control. In other words, the system had to 'grow' with the player to sustain the sensitivity of the biocybernetic loop. As the physiological computer game underwent this adaptation, the player notices that the system response has changed, and may adapt his or her behaviour accordingly. A sustained experience of physiological computing locks the player and the system into a co-evolutionary spiral [42], as the system adapts to the player and vice versa. Players are often highly motivated to understand the rules underlying game play in order to develop their skills, and it is imagined that most physiological computer games will eventually function as a source of biofeedback from the players' perspective. The logical outcome of speculation is that the value of physiological computer game software will be determined by its co-evolutionary potential (i.e. the capacity of the software to adapt in unpredictable ways over time), which determines both the quality and quantity of game time.

The interaction between the player and a physiological game should be considered as a closed-loop system. The behaviour of the control loop will shape the playing experience and the flexibility of the software will determine the co-evolutionary potential of the interaction.

5. CONCLUSIONS

Physiological computer games offer great scientific and economic potential. However, the development of physiological games must be based on a solid empirical and theoretical foundation. If the process of psychophysiological inference is ignored, players will be faced with gaming software that responds in an erratic or highly constrained fashion. The fidelity and range of the adaptive response is determined by complexity of the representation of the player. The adaptive potential of biocybernetic loop determines the quality of the human-computer interaction in the long-term.

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