A Control-Theoretic Approach to Adaptive Physiological Games

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ABSTRACT

This paper presents an adaptive biofeedback videogame that aims to maintain the player's arousal level at an optimum level by monitoring physiological signals and manipulating game difficulty accordingly. We use concepts from classical control theory to model the interaction between human physiology and game difficulty during game play. Based on this control model, we have developed a real-time car-racing game with adaptive game mechanics. Specifically, we utilized car speed, road visibility, and steering jitter as three mechanisms to manipulate game difficulty. We propose quantitative measures to characterize the extent to which these three game adaptations can manipulate the player's arousal. For this purpose, we used electrodermal activity (EDA) as a physiological correlate of arousal. We have validated our approach by conducting experimental trials with 20 subjects in both open-loop (no feedback) and closed-loop (negative feedback) conditions. Our results show statistically significant differences among the three game mechanics in terms of their effectiveness. Specifically, manipulating car speed provides higher arousal levels than modulating road visibility or vehicle steering. Finally, we discuss the theoretical and practical implications of our approach.

Author Keywords

Affective computing, physiological games, dynamic game balancing.

ACM Classification Keywords

H.1.2 User/Machine Systems (Human factors); H.5.2. Information interfaces and presentation: User Interfaces (Theory and methods)

General Terms

Design, experimentation, human factor.

INTRODUCTION

Physiological sensors have garnered a great deal of attention in the gaming research community [1]. Physiological variables such as heart rate, skin conductivity and even respiration are generally under autonomic (i.e., non-voluntary) control and therefore can provide an objective measure of the internal state of the player; as noted by Hettinger et al. [2] physiological sensors "*open an additional channel of communication from the user to the computer, albeit a largely unconscious one*". Thus, the integration of physiological sensors in videogames may enable new forms of gameplay as well as new applications beyond entertainment. As an example, physiological sensors may be used to improve the player's engagement with and immersive experience of the videogame, to adapt gameplay to the ability of each individual player, and to develop new health interventions that leverage the broad appeal of videogames to improve patient compliance.

In this work we explore physiological input for the purpose of controlling difficulty levels in videogames, with the explicit goal of maintaining a sustained level of arousal in the player. The majority of approaches to dynamic difficulty adjustment (also known as dynamic game balancing) use the player's performance on the game as the main measure of difficulty [3]. A classic example is the "rubber band" approach used in car-racing games (e.g., Mario Kart): players who fall behind in the race will encounter more bonuses (and fewer obstacles) than those who dominate the race. Using task performance is appealing because it can be integrated in the game without the need for additional hardware. However, it is not task performance but the emotional experience of the player that is critical in gameplay [4]. For this reason, a number of recent studies have begun to explore the use of physiological measures as a way to capture facets of the player's experience; these measures can then be transformed into control signals to adapt game parameters, in what has been described as a biocybernetic loop [5-7].

In this paper we propose a general framework to model the process of game adaptation and quantify the effectiveness of different game mechanics. Our approach is complementary to prior work on physiologically-driven game adaptation, which relied on user surveys/questionnaires and other subjective metrics to assess game mechanics and parameters [8]. Borrowing concepts from control theory [9], we model the player as a dynamical system whose output (varying arousal levels) must follow an external setpoint (constant arousal). This goal is achieved by measuring the player's arousal with a physiological sensor, computing its error with respect to the setpoint, and adapting the game difficulty so as to reduce the error. As will be described later in the paper, this type of model has several advantages. First, it allows us to simulate the behavior of the system under different parameter settings, results from which can help guide the game design/development process. Second, the model provides a compact parameterization of the system, which facilitates the evaluation of different game mechanics. Finally, it provides objective measures of system performance (error, oscillation) that are complementary to subjective and observation-oriented measures commonly used in game evaluations.

To validate our approach, we have developed an adaptive car-racing game and characterized three different game adaptation mechanics: visibility, steering, and speed. First, we test the system in an open-loop configuration; this allows us to calibrate the system to each individual player and evaluate the effectiveness of each game mechanics to bring about a change in the player's physiology. Then we evaluate the system in a closed-loop configuration where the game mechanics are modulated by a proportional feedback control law so as to maintain the player's arousal around a desired setpoint. We hypothesize that, under negative feedback, the better game mechanics will drive the player's arousal level to a value close to the setpoint (or small constrained/short cycle oscillations around it) [7]. Our approach uses phasic changes in electrodermal activity (skin conductance responses, or SCR) as a psychophysiological indicator of arousal. Implicit here is the assumption that the psychophysiological relationship is a one-to-one mapping [10, 11] and that there exists a reference physiological level which the control law and the game mechanics can target, i.e., the reference level is observable, and the player's SCR (though non-deterministic/stochastic) is controllable within a certain range [12].

RELATED WORK

Prior studies on affective computing have revealed a great potential for physiological information in enriching gaming experience [5]. The videogame industry has explored biofeedback gaming using various types of physiological sensors, including electroencephalography (brain-computer interfaces) electrodermal activity (galvanic skin response), electrocardiography, heart rate and respiration sensors, and electromyography (muscle activity) [13]. To date, however, biofeedback games have not gained much popularity from the gamer community and are still mostly constrained to laboratory settings. In a recent review of psychophysiological methods in gaming, Kivikangas et al. [1] note that many challenges still remain in the field of biofeedback games. Among them there is the absence of a commonly accepted theory on assessing game experience, which leads to fragmentation of biofeedback game designs and game studies. The authors also note that most prior psychophysiological findings are based on simple experimental tasks in constrained settings (e.g., using standardized pictures as emotional stimulation). This makes assessment of game parameters much harder since computer games are complex systems where interaction occurs at multiple levels and consists of spontaneous input and output. In fact, biofeedback gaming experiments are carefully designed so as to minimize the effect of the confounding factors. Further, typically there is no one to one mapping that converts physiological signal to level of game difficulty. All these points indicate the necessity for a formal way for comparing the game parameters.

Recently studies have begun investigating fundamental aspects of physiological games. Kuikkaniemi et al. [14] explored the influence of implicit and explicit biofeedback game in the context of a first-person shooter (FPS) game. Implicit feedback occurs when the game player is not aware that the game behavior is manipulated according to their physiological state; the player may sense the feedback mechanism but only at a subconscious level. In contrast, explicit biofeedback occurs when the player has conscious control over specific game dynamic. The authors used a within-subjects design where each person was exposed to both types of feedback; in the implicit feedback condition the experimenter did not inform the participants that the game dynamics were being modulated based on their physiological state, whereas in the (subsequent) explicit biofeedback condition players were informed that their arousal level controlled the speed of their character. The authors discovered significant increases of immersion only in the explicit biofeedback condition [14]. In a related study, Nacke et al. [13] investigated sensor mapping for two types of physiological signals: voluntary (direct) and involuntary (indirect). An example of direct (voluntary) control would be to use muscle activation or eye gaze, whereas an example of indirect (involuntary) control would be to use heart rate or skin conductivity. The authors conclude that direct input should be mapped intuitively into actions, whereas indirect input should be used to affect environmental variables of the game.

The subfield of adaptive automation is particularly relevant to our work. Adaptive automation [15, 16] is concerned with maintaining an optimal level of vigilance in tasks that combine human and automatic monitoring (e.g., flying an airplane). In these scenarios, a high degree of automation can reduce the operator's vigilance and engagement with the task, whereas low levels of automation can result in excessive workloads. To address this problem, adaptive automation operates as a negative feedback loop, where task allocation to the operator is increased if he becomes hypo-vigilant and is decreased whenever the operator's workload becomes too high. A number of physiological variables have been explored as correlates of attention, including measures of electroencephalography (EEG), electrocardiography (ECG), and electrodermal activity (EDA). In a classical study, Pope et al. [17] investigated several engagement indices based on EEG spectral power in the alpha and beta range. In this study, participants were asked to perform a tracking task that is analogous to those performed by crew-members in flight management. When the adaptive automation was run in a negative feedback loop (e.g., decreased vigilance lead to an increase in task demand), the engagement indices displayed short-cycle oscillations, whereas in a positive-loop configuration (e.g., decreased vigilance lead to a reduction in task demand) the engagement indices showed longer and more variable periods of oscillation, which proved the existence of a functional relationship between engagement index and task demands. In a more recent study, Boucsein et al. [18] evaluated autonomic system measures of vigilance as an alternative to EEG, which is impractical in commercial aviation scenarios. The measures included (1) non-specific skin conductance responses (NS.SCR), (2) NS.SCR combined with heart rate (HR), and NS.SCR combined with heart-rate variability (HRV). In this study, subjects were asked to complete a mission on a professional flight simulator, and their degree of arousal was used to modulate the amount of turbulences in the simulator. Results from this study indicated that autonomic measures (EDA, ECG) may also be used in adaptive automation. In particular, the combination of NS.SCR and HRV was found to be robust to motion artifacts: NS.SCR and HRV change in opposite directions with increasing task demands (e.g. NS.SCR increases while HRV decreases), so simultaneous increases in both variables can be dismissed since they are indicative of body movements or deep breathing rather than of changing task demands.

Videogames have also been combined with biofeedback techniques to treat specific conditions. Vilozni et al. [19] developed a video game that taught breathing skills to children; in the game, the player controlled an animated critter with their breathing, measured with a spirometer. Herndon et al. [20] developed a biofeedback-based game to help children with voiding dysfunction learn to control their pelvic floor muscles. By contracting or relaxing their muscles, the patients were able to control aspects of the game, such as shooting accuracy in basketball or distance travelled in a golf game. Leahy et al. [21] developed a game to teach deep relaxation to patients with irritable bowel syndrome, a condition to which stress is a major contributor. The game required patients to achieve increasing levels of relaxation, measured with a skin conductance sensor, in order to progress through a visualization of the digestive tract. Several commercial systems employ similar "game-like" strategies to make biofeedback more intuitive. In these systems, sensor signals are transformed into visually-pleasing graphics and animations; see e.g., [22]. While such elaborate biofeedback displays may be more appealing than visualizing raw sensor signals, much more could be gained if biofeedback was fully integrated into a dynamic game [23]. As an example, Sharry et al. [24] developed "Relax to Win," a biofeedback game to treat children with anxiety disorders. In the game, two players compete on a racing game in which the speed of the player's avatar (a dragon) increases with the player's ability to relax, as measured with a skin conductance sensor; however, only anecdotal evidence was provided to support the effectiveness of the game.

Rani et al. [6] compared two types of feedback to adjust game difficulty levels. The first approach (anxiety feedback) consisted of modulating game difficulty based on the physiological state of the player in a negative feedback loop; high levels of anxiety (as measured through electrocardiography, impedance cardiography, photoplethysmography, heart sounds, skin conductivity, peripheral temperature, and electromyography) would cause the difficulty level to drop, and vice versa. The second approach (performance feedback) consisted of varying the level of difficulty according to the player's performance in a positive feedback loop: high performance would lead to an increase in difficulty level state, and vice versa. In both cases, the game was allowed to switch among three difficulty levels states (easy, moderately difficult, and very difficult) using a finite state machine. Their result showed that the anxiety-feedback was more effective than the performance feedback in challenging the players, improving their performance, and lowering their anxiety.

SYSTEM OVERVIEW

An overview of the proposed system is shown in Fig. 1(a). The player interacts with a computer videogame while his/her physiological signals are measured with a wearable sensor. Physiological signals are converted into an index of arousal, which then drives a game-adaption engine that controls certain properties of the game. Our main challenges in implementing this system were to identify (1) reliable physiological correlates of arousal, and (2) game mechanics to manipulate the player's arousal. We also needed a videogame that would be intuitive and engaging, that would be amenable to adaptation, and (for experimental reasons) that would not require extended play time. From among the various game genres available in the market (e.g., strategy/puzzles, role playing, action/adventure, sports, racing, shooter, fighter, arcade) [25] we decided to focus on a car-racing game –see Fig. 1(b), because of its intuitive nature and ease of learning, its highly dynamic characteristics, and the multiple forms of adaptation that it enabled. To reduce the number of confounding factors, we modified the car-racing game such that the player was only required to control the steering.

The speed of the car at each position in the race track was variable (e.g. high for straight lines, low for chicanes) but predetermined; this nominal speed profile was obtained by recording a proficient car-racing player during an initial pilot study. In our study, we chose to explore three distinct types of adaptation: weather, steering, and speed.

Weather

Under this adaptation modality, we manipulated weather conditions (rain, snow, and fog) to affect road visibility. At 0% inclement weather, the environment represented a clear sunny day and visibility is perfect. At 50% inclement weather, visibility was reduced to approximately 10 meters. Finally, at 100% inclement weather the driver had a visibility of approximately 2 meters. Visibility at other difficulty levels was linearly interpolated from those three points. As visibility decreases, the player is forced to rely on subtle peripheral cues (guard rails, road surface markings) to guide the car. Weather conditions did not affect vehicle dynamics (e.g., adherence to the road).

(a)

(b)

(c)

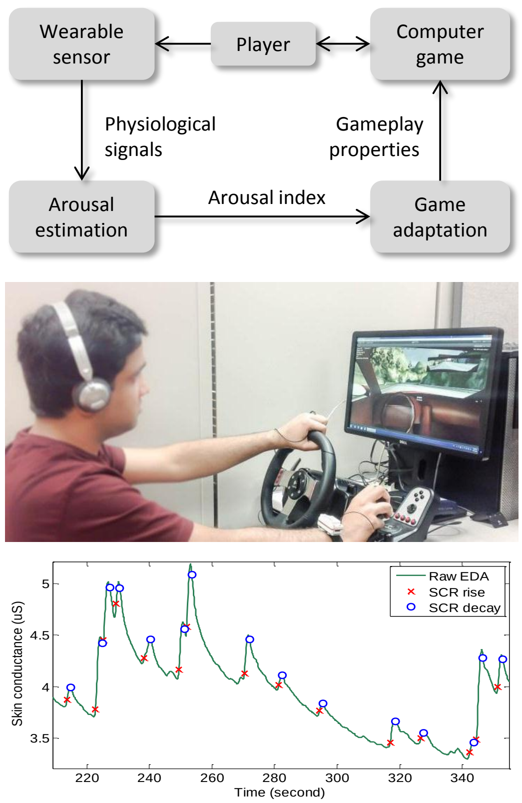

Fig. 1. (a) Block diagram of the adaptive physiological game. (b) A participant playing the car-racing game. (c) Recording of electrodermal activity (EDA) and detected SCR events.

Steering

Under this adaptation modality, we introduced random disturbances to the steering direction in the form of additive nose. At 0% disturbance, no noise was added to the steering signal. At 50% disturbance, an angular jolt of 45 degrees was added to the player's intended steering direction; at 100% disturbance, an angular jolt of 90 degrees was added. Angular disturbances at other % difficulty levels were linearly interpolated from those three points. The direction (clockwise or counter-clockwise) of the disturbance was chosen at random and the noise was added every 0.5 seconds. Manipulating the steering reduced the sense of control of the player.

Speed

Under this adaptation modality, we manipulated the speed of the car through a multiplicative factor. This was done so as to reduce the complexity of the game and the chances of learning effects. At 100% speed, the velocity of the car was the nominal speed at that location, as determined during the initial pilot study (see above). The speed was 80mph at 100% level. At 50% speed, the velocity of the car was the nominal speed at that location reduced by a factor of 0.75 (55 mph). Finally, at 0% speed, the velocity of the car was the nominal speed at that location reduced by a factor of 0.5 (40 mph). Manipulating the speed allowed us to adjust the difficulty of the game in a more ecological way than altering weather conditions or the vehicle's steering.

We estimate the arousal level of players through their electrodermal activity (EDA), popularly referred to as galvanic skin response. EDA is advantageous for this purpose because the skin is exclusively innervated by the sympathetic nervous system, whereas most other organs are under the influence of both autonomic branches. Thus, EDA is highly sensitive to emotional arousal (e.g., startle, fear, anger) [26]. The EDA response consists of two characteristic components, (i) a slowly changing offset known as the skin conductance level (SCL), and (ii) a series of transient peaks known as skin conductance responses (SCR) [27] that occur in reaction to startle events (i.e., an unexpected loud noise) but also spontaneously, in which case they are referred to as non-specific (NS-SCR) [28]. SCLs are highly subject-dependent and can also be influenced by the choice of electrode site and conductive gel. Furthermore, in the presence of an SCR, measurement of the baseline SCL can be difficult. Instead, we use the number of SCRs within a fixed time window ($T = 30$ sec) as a measure of arousal. Fig. 1 (c) shows a typical EDA signal and the onset/offset of individual SCRs, detected by applying a threshold to the time derivative of the raw EDA signal.

CONTROL THEORETIC PARADIGM

As discussed earlier, we use concepts from classical control theory to model the process of adapting the videogame in response to the player's arousal level. As illustrated in Fig. 2(a), the basic building blocks of a control system are: (i) the plant or system we wish to control, (ii) a sensor, which measures the state of the plant, and (iii) a controller, which provides an input to the plant so as to minimize the difference between desired (setpoint) and actual (measured) output. As an example, consider the problem of maintaining the temperature in a home. In this case, the plant is the AC/heating system, the controller is the thermostat, and the sensor is a thermistor (commonly integrated in the thermostat).

Control theory provides the mathematical tools to design the controller to meet specific performance criteria such as rise time (i.e., responsiveness) and damping (i.e., lack of oscillation). As an example, the controller may produce an output that is proportional to the measured error, to the derivative of this error (to provide damping), to the integral

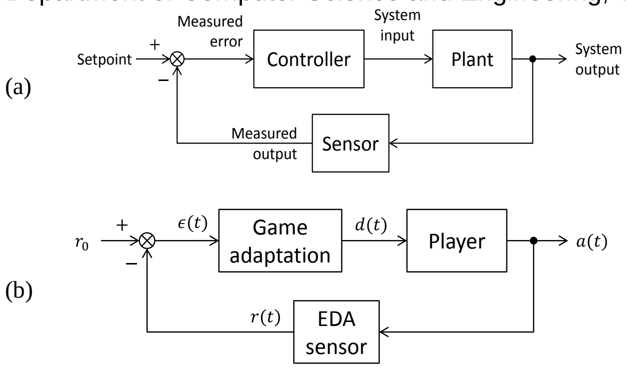

Fig. 2. Block diagram of (a) a classical feedback control system, and (b) our adaptive physiological game.

of the error (to reduce residual steady-state errors) or any combination of the three, leading to what is known as PID control (proportional-integral-derivative).

Fig. 2(b) shows the generic block diagram when applied to the adaptive physiological game. In this case, the player is the "plant" whose output (arousal) we seek to maintain constant. The sensor in the feedback loop is the EDA sensor, which converts the player's arousal into a measurable variable, in this case the number of SCRs per unit of time. Finally, the game-adaptation engine takes the deviation between desired and actual arousal level and modulates the game parameters (visibility, steering disturbances, and speed) to shape the future physiological response of the player. Thus by choosing an appropriate setpoint and control law, such a feedback system can be used to elicit desired physiological response and/or performance levels [5, 29].

The block diagram in Fig. 2(b) is an example of a feedback system with a human in the loop. Although there is no well-defined transfer function of the human [8] (the plant), principles from classical control theory can guide us in designing the feedback controller, modeling the player-game interaction, and assessing the performance of the game mechanics. In this work we utilize negative feedback loop as it leads to higher level of stability [9] and prevents saturation of user's physiological response. Saturation in the physiological response can refer to a number of issues including boredom, tiredness, lack of concentration etc. which are detrimental to gaming experience.

To illustrate the benefits of our proposed control-theoretic approach, let's consider the following simplified model:

$$\boldsymbol{r(t) = r(t-1) + k_F d(t)} \qquad (1)$$

$$\boldsymbol{d(t) = d(t-1) - k_B \epsilon(t)} \qquad (2)$$

$$\boldsymbol{\epsilon(t) = r(t) - r_0} \qquad (3)$$

where $d(t) \in [-1,1]$ is the game's difficulty level at time t, $r(t) \in [0,1]$ and r_0 are the player's measured EDA response (i.e., number of SCRs per unit of time) and desired response, respectively, and $\epsilon(t)$ is the error (difference between both).

Equation (1) is the plant model, and states that the player's increase in EDA at time t is proportional to the increase in game difficulty at that time; the forward proportionality constant k_F captures the effectiveness of the particular game mechanics in shaping the player's arousal level (larger values of k_F being better). Equation (2) is the controller model, which in this example is a simple proportional control law: the larger the error (difference between the setpoint and desired arousal) the larger the change in difficulty level, with the backward proportionality constant k_B controlling how quickly the game difficulty will change. Large value of k_B can reduce steady state errors quickly, but can also result in large oscillations and even instability [7].

Simulation results

We will illustrate the behavior of the model by simulating the experimental protocol that will later be used in the user studies described in the Experimental Protocol section. In a first experiment, the player is asked to play the car-racing game in an open-loop configuration at a few predetermined difficulty levels; this allows us to calibrate the game, i.e., determine the characteristic number of SCRs for each player under low, medium and high difficulty conditions. Simulation results are shown in Fig. 3(a) for two values of k_F (low, high) when the game difficulty level is driven by the pulse sequence$\{0, 50, 0, 100, 0, 50, 0, 100, 0\}$%. For high k_F the number of SCRs increases sharply upon the introduction of the first pulse (50% difficulty) and begins to decay once the difficulty level is brought back to 0%; for low k_F the increase is more gradual and less pronounced. A similar behavior is observed for the second pulse (100% difficulty), though in this case the number of SCRs is higher due to the increased difficulty level. Despite its simplicity, results from this simulation are remarkably close to those we will later observe experimentally. In a second experiment, the player is then asked to play the car-racing game in a closed-loop configuration with a setpoint equal to the number of SCRs observed at 50% difficulty in the initial open-loop experiment. Simulation results are shown in Fig. 3(b) for low and high values of k_B; in this case we kept k_F constant to a high value ($k_F = 0.9$). As shown in Fig. 3 (b) and (c), high values of k_B lead to larger changes in game difficulty in response to the player's arousal, which in turn leads to more frequent and higher oscillations in arousal and game difficulty. In contrast, low values of k_B lead to fewer and less pronounced subtle oscillations, which are likely to be more desirable to the player.

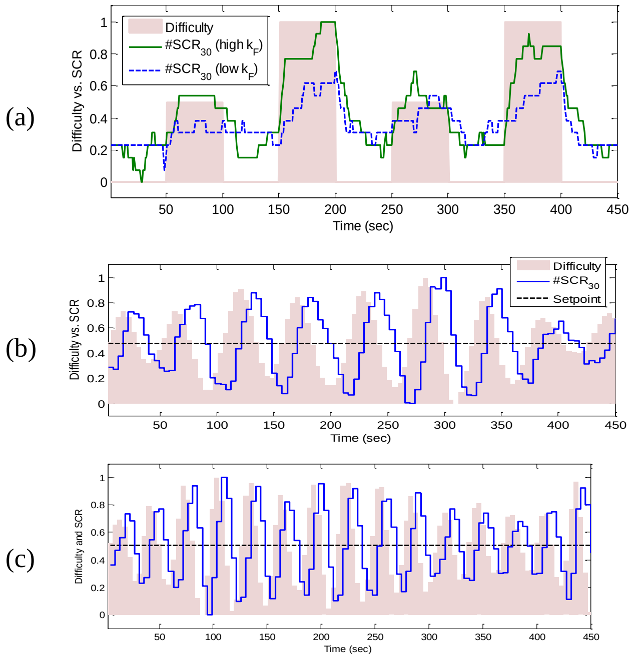

Fig. 3 (a) Open-loop simulation for high $k_F = 0.9$ and low $k_F = 0.5$. Closed-loop simulation for (b) low k_B=0.1 (k_F=0.9) and (c) high k_B=0.9 (k_F=0.9).

EXPERIMENTAL

Gaming platform

To validate our game-adaptation approach, we developed a car-racing game using the Unity game development platform [30]. Specifically, we modified the car tutorial [31] to incorporate physiological feedback from an EDA sensor. As described in the System Overview section, we implemented three types of game mechanics for adaptation: inclement weather, steering disturbances, and speed scaling. Fig. 4 shows the effect of inclement weather on road visibility; at the lowest visibility the player has to rely on subtle peripheral cues (e.g., guardrails, road markings) to determine the vehicle's orientation.

Physiological measurement

Measurements of electrodermal activity were performed with a FlexComp Infinity encoder (Thought Technology Ltd.) and streamed to the game engine via TCP/IP using the vendor's TTL Connection Server SDK. Disposable Silver/Silver Chloride (AgCl) electrodes were placed at the palmar and hypothenar eminences in palm of the player's non-dominant hand; this recording site was chosen because it has been shown to provide excellent recordings of electrodermal activity [32]. A drawback of the palms (as well as other common EDA recording sites such as phalanges) is that electrodes can disrupt regular activities such as grasping. For this reason, participants were instructed to use only the dominant hand to control the steering wheel so as to minimize motion/pressure artifacts in EDA signal. Use of other recording sites such as wrist or ankle may be less obtrusive [33] but are yet to be validated in the context of biofeedback game.

Fig. 4. Effect of inclement weather (IW) on road visibility. (a) Under 0% IW, visibility is perfect. Visibility drops to 10m and 2m under (b) 50% and (c) 100% IW, respectively.

Experimental protocol

We conducted experimental trials as part of an independent study with each participant playing a single (randomly assigned) game mechanics. We adopted this this between-subjects design to avoid order effects (such as learning or fatigue). Twenty students participated for the study (7 for weather, 7 for speed, 6 for steering). The ages of the participants ranged between 18 and 33 years. We received approval from the Institutional Review Board (IRB) prior to the study and consent from individual participant was received before the session. Participants played the game on a 22" wide LCD monitor using a Logitech G27 Racing Wheel. No background music was played during the game other than car engine and event-related (e.g. collisions) sounds.

The experiments were conducted in two phases on the same day: open loop (phase 1) and closed loop (phase 2). During both phases we recorded the players' EDA. During phase 1 (open-loop) users played the game with a particular mechanics (weather, speed or steering) at three different difficulty levels following the step sequence $\{0, 50, 0, 100, 0, 50, 0, 100, 0\}\%$, each step lasting one minute. Steps of 0% difficulty were interleaved to minimize roll over effects between the 50% and 100% difficulty levels. The open-loop calibration session ran for 8 minutes. During this phase, the player's EDA did not alter the game's difficulty level. Instead, the purpose of phase 1 was to collect the player's EDA response under a range of arousal levels. From here, we calculated the average number of SCRs over a 30-second window ($\#SCR_{30}$) and used it as the setpoint for the closed-loop experiments in phase 2.

During phase 2 (closed-loop), participants played the game for two 5-minute sessions with a two-minute break in between. During this time, the game difficulty was adapted in response to the player's EDA so as to maintain the setpoint (i.e., the average $\#SCR_{30}$ during phase 1) using the control law in equation (2) with $k_B = 1$. Phase 2 allowed us to evaluate the effectiveness of the feedback loop in maintaining the player's arousal level at the desired value.

RESULTS

Open-loop

Fig. 5 shows experimental results for one subject during phase 1 (speed). These results have a striking resemblance to those obtained during the simulation study; see Fig. 3a. We assessed the effectiveness of the three game mechanics in eliciting the desired response using three criteria: total number of SCRs, game effectiveness (k_f), and rise time.

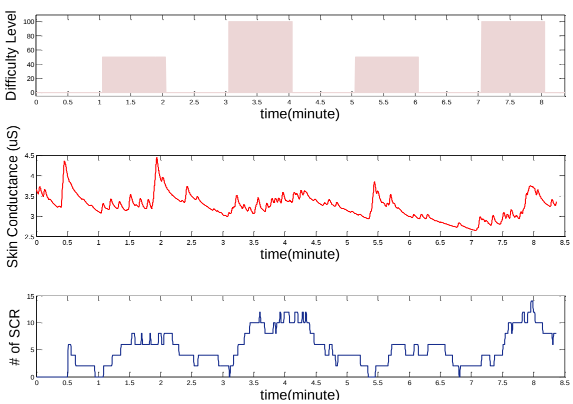

Fig. 5 Experimental results during the open-loop phase 1 (subject P1; speed): (top) difficulty, (middle) raw EDA response, (bottom) average #SCRs over a 30-second window.

Number of SCRs

Fig. 6 shows the average number of SCRs over a 30-second window ($\#SCR_{30}$) for the three game mechanics at 50% and 100% difficulty. The 0% response is not shown because the three mechanics are equivalent at that level. This allowed us to treat each player's $\#SCR_{30}$ at 0% as their physiological baseline and subtract it from their $\#SCR_{30}$ at 50% and 100% difficulty.

As shown in Fig. 6, the speed mechanics elicited higher $\#SCR_{30}$ on average than steering and weather, which suggests that speed is the most effective of the three mechanics. However, steering shows the largest change in $\#SCR_{30}$ when going from 50% to 100% (it doubles) whereas the other two mechanics seem to be tapering off. This suggests that there is a non-linear relationship between the difficulty level in our percentage-scale and the challenge perceived by the player.

Condition	Open-loop phase		Closed-loop phase	
	k_F	Rise time (SD)	Average #SCRs (SD)	Mean Squared Error (SD)
Weather	1.76	38.8 (18.8)	3.22 (0.59)	2.92 (1.70)
Speed	2.6	35.5 (11.3)	4.6 (0.41)	2.75 (1.46)
Steering	1.99	40.3 (13.3)	3.8 (1.14)	2.91 (1.75)

Table 1. Summary statistics from the experimental trials

Steering also has higher variance in $\#SCR_{30}$ than the other two mechanics. The most likely explanation for this result is that abrupt changes are introduced to the steering that require instant action from user, whereas changes in the other two mechanics can be introduced more gradually.

Moreover, at constant difficulty levels, players in the steering condition continue to experience periodic disturbances in the steering (with amplitude proportional to difficulty), whereas players in the speed and weather conditions do not experience noticeable changes in the game.

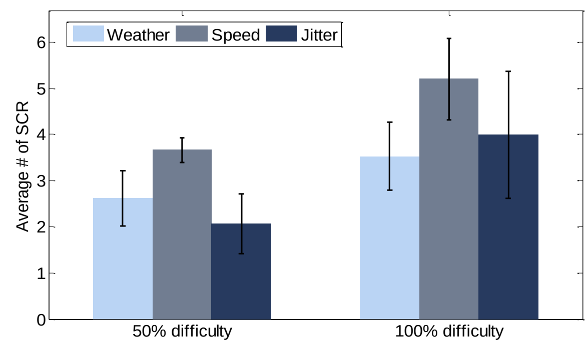

Fig. 6 Average SCR (normalized) across all subjects for the three game mechanics at 50% and 100% difficulty level.

Measurement of game effectiveness parameter k_f

We also compared the three game mechanics in terms of their game effectiveness parameter k_F, as defined in equation (1). For each game mechanics, we computed k_F as the slope of the $\#SCR_{30}$ data in Fig. 6 over the range 0-100%. As shown in Table 1 the speed condition has the largest k_F coefficient, indicating that it is the most effective game mechanics, whereas weather is the least effective.

Rise time

Along with the performance criteria $\#SCR_{30}$ and k_F, we also calculated the rise time of $\#SCR_{30}$, measured as the time taken to reach the highest peak in $\#SCR_{30}$ after a step in difficulty from 0% to 100%. The rise time can be a good indicator of responsiveness, lower rise time indicating a swift response. Statistics for the rise time across subjects for the three game mechanics are shown in Table 1. These results indicate that the speed mechanics provides the fastest response (lowest rise time).

ANOVA results

We evaluated the statistical significance of these results with a 2-way ANOVA, with game mechanics and difficulty as main effects, and $\#SCR_{30}$ as the dependent variable. Hence, the null hypotheses were that (i) increasing difficulty levels do not affect $\#SCR_{30}$, 2) the three modes of adaptation cause similar changes in $\#SCR_{30}$, and 3) there are no interactions among the two factors (i.e., relative ordering of mechanics does not change between 0%, 50% and 100%). The p values for game difficulty and game mechanics were 1.75×10^{-8} and 0.025, respectively. The interaction p value between these two factors was 0.716, which might indicate the interaction between two factors. This implies that it is important to study the mapping between difficulty level and individual game mechanics. We also performed 1-way ANOVA to compare the three mechanics on the basis of rise times and obtained a p-value of 0.0178. These results thus reject the null hypotheses with high confidence and indicate that the differences in game mechanics and difficulty levels are statistically significant. These results also allow us to conclude that speed is the most effective mechanics in terms of modulating the arousal level of the player.

Closed loop

In closed-loop operation, the goal of the controller is to manipulate the game difficulty so as to maintain the player's arousal level around a setpoint. This setpoint is obtained as the average $\#SCR_{30}$ from the open-loop phase, as described in the Experimental section. We use two metrics to evaluate the three game mechanics in a closed-loop configuration: (1) mean squared tracking error and (2) total number of SCRs. From our earlier discussion (see Simulation studies) a better game mechanics would result in lower tracking errors as well as fewer oscillations around the setpoint.

Number of SCRs

Statistics for the three game mechanics are showed in Table 1. The speed mechanics has the largest $\#SCR_{30}$ as well as the lowest standard deviation whereas steering has the largest standard deviation and weather has the lowest total number of SCRs. These results are consistent with those obtained in the open-loop phase, and again suggest that speed is the most effective mechanics. A 1-way ANOVA (with game mechanics as the factor) shows that this result is marginally significant($p = 0.051$).

Tracking errors

Finally, we compared the tracking errors incurred by each controller in terms of mean squared error (MSE) between the setpoint and the $\#SCR_{30}$ elicited from the player. As shown in Table 1, the speed mechanics had the lowest error (averaged across subjects) when compared to the other two game mechanics. However, a 1-way ANOVA on the MSE shows that these differences are not statistically significant ($p = 0.514$). As will be discussed in the next section, this result suggests that a more elaborate control law (i.e., incorporating derivative and integral terms should be used) should be explored in future studies.

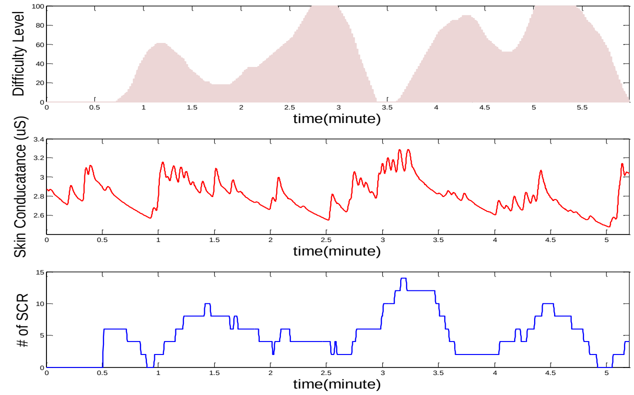

Fig. 7 Closed loop data (Speed mechanic from subject P1)

DISCUSSION AND CONCLUSION

In this paper we have presented a theoretically-motivated approach for the design and analysis of adaptive physiological games. The approach is inspired by basic principles from classical control theory, and in particular by the concept of negative feedback. In contrast with previous studies in adaptive automation, our model parameters are not aimed at assessing the performance of a human operator. Rather, these parameters provide a quantitative measure with which different mechanics can be compared in the context of the racing game, namely, in terms of how effectively they can elicit a physiological response from the player.

To develop a good understanding of the model, we first performed simulation studies in open-loop and closed-loop configurations. Findings from these simulations were then corroborated experimentally through user studies. These results suggest that our model could be used to analyze the sensitivity of the system to its various components (e.g., controller, game mechanics, physiological measures, etc.). As an example, a designer interested in using heart rate variability (HRV) instead of electrodermal activity may be able to incorporate the dynamic properties of HRV into the model, study its effects, and design a suitable controller.

Our experimental results show that speed adaptation is more effective than the other two mechanics. Specifically, speed mechanics elicited a higher number of SCRs and well as the smallest rise times in an open-loop configuration; it also had the lowest mean-squared-error in a closed-loop configuration. These findings are consistent with work by Min et al. [34] which argues that states of arousal and relaxation can be identified by observing the physiological variables in dynamics environment. Specifically, the authors studied the autonomic response of car drivers as a function of the vehicle's speed. The authors found that sympathetic activation depended highly on the speed as compared to the remaining factors; this would explain why subjects in our experiments had higher EDA on the speed condition –the skin is exclusively innervated by the sympathetic nervous system.

An alternative explanation for our results may come from studies on the relationship between perceived control and arousal. As an example, Wise and Reeves [35] studied the skin conductance response of participants viewing a series of photographs. Participants in the treatment group had control of when the next picture would be presented, whereas participants in the control group did not have such control (the computer controlled the display). Their results show that subjects in the treatment group (those who had control) had higher levels of arousal, as measured by their skin conductivity. Thus, it is possible that, in our study, participants in the speed condition displayed high EDA because of their perceived sense of full control, whereas participants in the jitter condition had little control over the random disturbances in the steering.

FUTURE WORK

In this study we used EDA as the physiological correlate of arousal. With the EDA signal, the proportional biofeedback controller was able to drive the SCR signal towards the desired value. However, it still remains to be tested whether other psychophysiological indices (e.g., HRV) may be able to produce similar effects. HRV would be particularly appealing in ambulatory settings because it can be computed from heart-monitors, which can be worn inconspicuously and, unlike EDA sensors, do not interfere with normal activities (e.g., grasping, typing). Our study also used a proportional controller for modulating the game parameters. Adding an integral and derivative component (a PID controller) may, theoretically, further reduce the rise time, and decrease oscillations and settling time of the system. The performance of other controller and their mappings with individual game mechanics also needs to be studied.

In this paper, we presented a real-time biofeedback gaming system that adapts game mechanics to elicit a desired physiological response from the player. Here we compared three game mechanics for a racing game and used a proportional feedback controller. Further work is needed to determine whether other feedback controllers (e.g. proportional-integral, proportional-integral-derivative) may be able to achieve lower tracking errors and more stable EDA than proportional control.

Another direction of future work is in simultaneous adapting multiple game mechanics. Combined with multimodal physiological sensing, this would lead to multi-input-multiple output (MIMO) systems. Development of such systems would require a good understanding of the mapping between difficulty levels for each of mechanics and the corresponding physiological indices.

Biofeedback videogames can also be modified to be used in the domains of health care and stress regulation. A tool for stress self-regulation would require a positive feedback system, as opposed to the traditional negative feedback loop. In positive feedback games, the player may be rewarded (e.g., higher scores, more game features) for staying calm and penalized for displaying high arousal. As a result, the user must learn to regulate their arousal response in the presence of a stressor, a skill that may transfer better to real-life scenarios than traditional relaxation techniques.

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