A Control-Theoretic Approach to Adaptive Physiological Games

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***Abstract*—We present an adaptive biofeedback game that aims to maintain the player's arousal level by monitoring physiological signals. We use concepts from control theory to model the interaction between human physiology and game difficulty during gameplay. We validate the approach on a car-racing game with real-time adaptive game mechanics. Specifically, we use car speed, road visibility, and steering jitter as three mechanisms to manipulate game difficulty. We propose quantitative measures to characterize the effectiveness of these game adaptations in manipulating the player's arousal. For this purpose, we use electrodermal activity (EDA) as a physiological correlate of arousal. Experimental trials with 20 subjects in both open-loop (no feedback) and closed-loop (negative feedback) conditions show statistically significant differences among the three game mechanics in terms of their effectiveness. Specifically, manipulating car speed provides higher arousal levels than changing road visibility or vehicle steering. Finally, we discuss the theoretical and practical implications of our approach.**

Keywords—Physiological games, dynamic game balancing, control theory.

I. Introduction

Physiological sensors have garnered a great deal of attention in the gaming research community [1-5]. Many physiological variables are under autonomic control (i.e., involuntary), and therefore can provide objective measures of the player's affective state [2]. As noted by Hettinger et al. [6] physiological sensors "*open an additional channel of communication from the user to the computer, albeit a largely unconscious one*". Thus, physiological sensors enable new forms of gameplay and new applications beyond entertainment; as an example, they may be used to improve engagement and immersion, to adjust game difficulty to the player's skill level, and to develop game-like health interventions.

To date, however, biofeedback games have not gained much popularity from the gaming community and are still mostly constrained to laboratory settings [1]. Part of the issue stems from the lack of a broadly accepted theory on how to assess game experience, which leads to a fragmentation of biofeedback game research. In turn, this makes assessment of game parameters much harder since computer games are complex systems where interaction occurs at multiple levels. In addition, mapping physiological signals to game difficulty levels is not trivial.

In this work, we propose a general framework to model the process of game adaptation, with the explicit goal of maintaining a sustained level of arousal in the player. 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). Specifically, the control law manipulates the game's difficulty level so as to maintain a sustained arousal level, as measured by electrodermal activity (EDA). Our approach has several advantages. First, it allows us to simulate the behavior of the system under different parameter settings, which can help guide the game 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 often 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. Our evaluation consists of two steps. 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 that maintains the player's arousal around a desired setpoint.

The rest of the paper is organized as follows. Section II summarizes prior work on integrating physiological sensors with videogames. Section III describes our modeling methodology based on control theory. Section V describes the adaptive videogame we developed to validate our model. Section VI presents results from simulation as well as user studies. Finally, section VII summarizes our findings and provides direction for future work.

II. Related work

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 [7]. A classic example is the "rubber band" 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 [8]. For this reason, recent studies have explored 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

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what has been described as a biocybernetic loop [5, 9, 10].

Rani et al. [5] compared two approaches to adjust game difficulty: anxiety-based and performance-based. The first approach modulated game difficulty based on the player's physiological state in a negative-feedback loop: high levels of anxiety reduced game difficulty, and vice versa. The second approach varied difficulty levels based on the player's performance in a positive-feedback loop: high performance increased difficulty levels, and vice versa. The authors found that anxiety-based feedback was more effective than performance-based feedback in challenging players, improved their performance, and lowered their anxiety. More recently, Kuikkaniemi et al. [11] explored two types of biofeedback (implicit vs. explicit) in a first-person shooter game. Implicit feedback occurs when the 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 discovered significant increases of immersion only in the explicit biofeedback condition.

In recent years, videogames have been identified as potential learning tools [12] and have been combined with biofeedback techniques to treat specific medical conditions. Vilozni et al. [3] developed a videogame that taught breathing skills to children; in the game, the player controlled an animated critter with their breathing, measured with a spirometer. Leahy et al. [13] developed a game to teach deep relaxation to patients with irritable bowel syndrome, a condition to which stress is a major contributor. 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. 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 [4] . As an example, Sharry et al. [14] developed a racing game for children with anxiety disorders; in the game, the speed of the player's avatar (a dragon) increases with the player's ability to relax, as measured through EDA. However, only anecdotal evidence was provided to support the effectiveness of the approach.

III. Control Theoretic Paradigm

We use concepts from classical control theory to model the process of adapting the videogame in response to the player's arousal. As illustrated in Fig. 1 (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. 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 of the error (to reduce residual steady-state errors) or any combination of the three, leading to

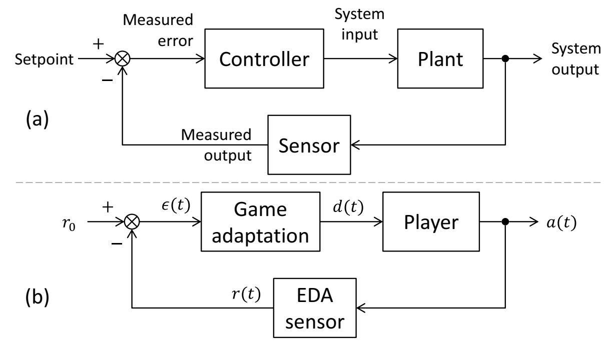

Fig. 1. Block diagram of (a) a classical feedback control system, and (b) our adaptive physiological game.

a PID (proportional-integral-derivative) control.

Fig. 1 (b) shows the generic block diagram when applied to an adaptive physiological game. In this case, the player is the "plant" whose output (arousal) we seek to maintain constant around a setpoint. The sensor in the feedback loop is the EDA sensor, which converts the player's arousal into a measurable variable. Finally, the game-adaptation engine takes the deviation between desired and actual arousal level and modulates the game parameters 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 [9].

The block diagram in Fig. 1 (b) is an example of a feedback system with a human in the loop. Although there is no well-defined transfer function for the human [15], 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. To illustrate the benefits of our control-theoretic approach, consider the following simplified model:

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

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

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

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[1] and desired response, respectively, and $\epsilon(t)$ is the error (difference between both).

Eq. (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 the time; the forward proportionality constant k_F captures the effectiveness of a particular game mechanics in shaping the player's arousal level (larger values of k_F being better). Eq. (2) is the controller model, which in this example is a 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 values of k_B can reduce steady state errors quickly, but

[1] As we will see in section IV.B, we use the number of skin conductance responses (SCRs) as the measure of electrodermal activity.

(a)

(b)

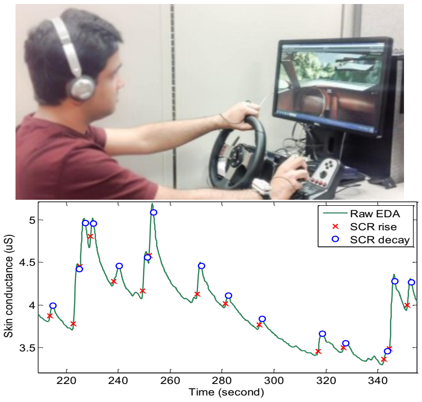

Fig. 2. (a) A participant playing the car-racing game. (b) EDA recording and detection of SCR events.

can also result in large oscillations and even instability [10].

IV. System overview

To validate our approach, we needed a videogame that would be intuitive, engaging, and amenable to adaptation. From among the various game genres (e.g., strategy, role playing, action/adventure, sports, racing, shooter, fighter, arcade) [16] we decided to focus on car-racing games, because they are intuitive, easy to learn, highly dynamic, and enable multiple forms of adaptation. For this purpose, we adapted an open-source racing game [17] to incorporate physiological feedback from an EDA sensor –see Fig. 1 (b). In an initial study, however, players found it difficult to control both the speed and direction of the car simultaneously; thus, we modified the game such that the player was only required to control the steering. This technique is called automatic acceleration and is commonly used in mobile racing games; the speed of the car at each position in the race track is different (e.g. high for straight lines, low for chicanes) but predetermined. We obtained a nominal speed profile for the circuit by recording 10 game plays of a proficient player during a pilot study.

A. Game adaptation mechanics

We implemented three different types of game adaptation: weather, steering, and speed. In the *weather* modality, we manipulated weather conditions (rain, snow, and fog) to affect road visibility. At 0% inclement weather, the environment represented a clear sunny day with perfect visibility. 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).

In the *steering* modality, we introduced random disturbances to the steering direction in the form of additive noise. 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 of the disturbance (clockwise or counter-clockwise) was chosen at random and the noise was added every 0.5 seconds. Manipulating the steering reduced the player's sense of control.

In the *speed* modality, we linearly manipulated the speed between 40-80 mph through a multiplicative factor on the predetermined speeds for the racing circuit, obtained from the pilot study. At 100% difficulty, the speed of the car followed the nominal speed for that location. At 50% speed, the velocity of the car was the nominal speed at that location reduced by a factor of 0.75. Finally, at 0% speed, the velocity of the car was the nominal speed at that location reduced by a factor of 0.5. Manipulating the speed allowed us to adjust the game difficulty in a more intuitive way than altering weather conditions or the vehicle's steering.

B. Physiological measure of arousal

We estimated the players' arousal through their electrodermal activity (EDA). EDA consists of two basic 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) [18] 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) [19]. SCLs are subject-dependent and can 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. In our pilot studies we found SCRs to be more responsive to the game dynamics than other physiological indicators including heart rate and heart rate variability (HRV). For these reasons, we used the number of SCRs within a fixed time window ($T = 30\,\text{sec}$) as a measure of arousal. Fig. 2 (b) 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.

V. 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 between-subjects design to avoid order effects such as learning or fatigue. Twenty students (age 18-33 years) participated in the study (7 for weather, 7 for speed, and 6 for steering). We received approval from the Institutional Review Board prior to the study and consent from individual participant was received before the session. Participants played the game on a 22" LCD using a Logitech G27 racing wheel. No background music was played during the game other than car engine and event-related sounds (e.g. collisions). EDA was measured with a FlexComp Infinity (Thought Technology Ltd.) and streamed to the game engine via TCP/IP. Disposable AgCl electrodes were placed at the palmar and hypothenar eminences in palm of the player's non-dominant hand [20]. To avoid motion/pressure artifacts, participants were instructed to use only the dominant hand to control the steering wheel.

The experiments were conducted in two phases on the same day: open loop (phase 1) and closed loop (phase 2). During phase 1, 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. Blocks of 0% difficulty were interleaved to minimize rollover effects between the 50% and 100% difficulty levels. The open-loop calibration session ran for 8 min. During this phase, the player's EDA did not alter the game difficulty level. Instead, the purpose of phase 1 was to collect the player's EDA response under a range of difficulty levels. From here, we calculated the average number of SCRs over a 30-sec window ($\#SCR_{30}$) and used it as the target setpoint for the closed-loop experiments.

During phase 2 (closed-loop), participants played the game for two 5-min sessions with a 2-min break. During this time, 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 eq. (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.

VI. Results

A. Simulation results

First, we illustrate the behavior of the system by simulating the model in eqs. (1-3). Results for phase 1 (open loop) are shown in Fig. 3 (a) for two values of k_F (low, high). Here, the game difficulty level is driven by the step 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.

Results for phase 2 (closed loop) are shown in Fig. 3 (b-c) for low and high values of k_B; here we kept k_F constant to a high value ($k_F = 0.9$). High values of k_B lead to larger changes in game difficulty in response to the player's arousal, which in turn leads to fast oscillations in arousal and game difficulty. In contrast, low values of k_B lead to fewer oscillations, which are likely to be more desirable to the player. Despite its simplicity, results from this simulation are remarkably close to those we observe experimentally, as we see next.

B. Experimental results: open loop

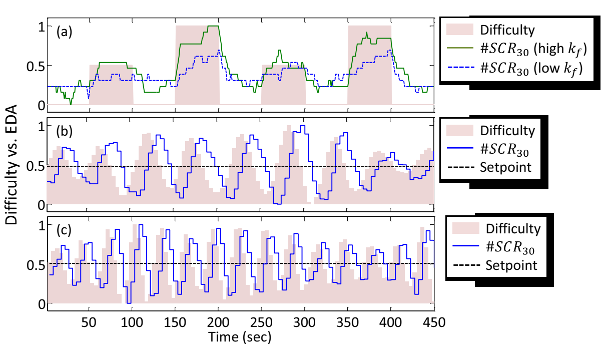

Fig. 3 (a) Open loop simulation for high vs. low game effectiveness (high $k_F = 0.9$; low $k_F = 0.5$). (b) Closed loop simulation for slow difficulty change (low $k_B = 0.1$; $k_F = 0.9$) and (c) Closed-loop simulation for fast difficulty change (high k_B=0.9; k_F=0.9).

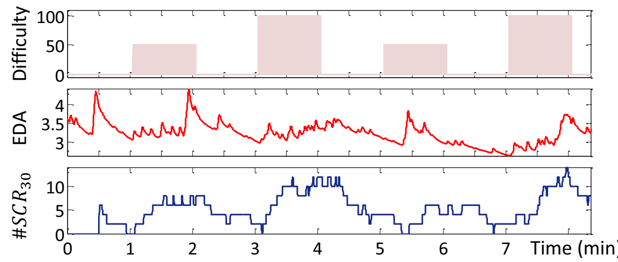

Fig. 4 Experimental results during the open-loop phase 1 (subject P1; speed): (top) difficulty, (middle) raw EDA response, (bottom) average #SCRs over a 30-second window.

Fig. 4 shows experimental results for one subject during phase 1 under speed adaptation; notice the striking resemblance with the $\#SCR_{30}$ trajectories in the simulation study of Fig. 3 (a). We assessed the effectiveness of the three game mechanics in eliciting the desired physiological response using three criteria: arousal ($\#SCR_{30}$), game effectiveness (k_f), and rise time. Fig. 5 shows the players' arousal for the three game mechanics at 50% and 100% difficulty. The 0% response is not shown since the three mechanics are equivalent at that level. Thus, we treat each player's $\#SCR_{30}$ at 0% as their physiological baseline and subtract it from their $\#SCR_{30}$ at 50% and 100% difficulty. 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) compared to the other two mechanics. This suggests that there is a non-linear relationship between the difficulty level in our percentage-scale and the challenge perceived by the player. Steering also has higher variance in $\#SCR_{30}$ than the other two mechanics. The most likely explanation for this result is the nature of the steering adaptation. This adaptation introduces abrupt changes in the steering that require immediate action from the player, whereas the other two mechanics introduce changes more gradually. Moreover, even during phases of constant difficulty levels, players in the steering adaptation group continue to experience periodic but random disturbances in the steering (with amplitude proportional to difficulty); in contrast, players in the speed and weather conditions do not experience noticeable changes in the game when the difficulty level is fixed.

We also compared the three game mechanics in terms of their game effectiveness parameter k_F, as defined in eq. (1). For each game mechanics, we computed k_F as the slope of the

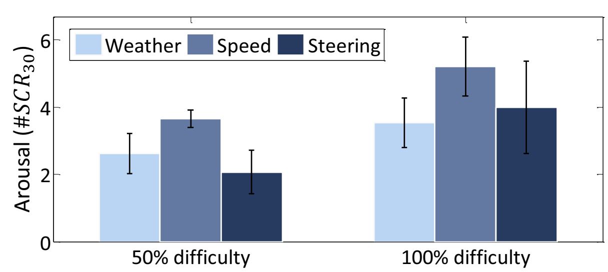

Fig. 5 Average SCR across all subjects during open-loop for the three game mechanics at 50% and 100% difficulty level (normalized by subtracting baseline SCR at 0% difficulty level).

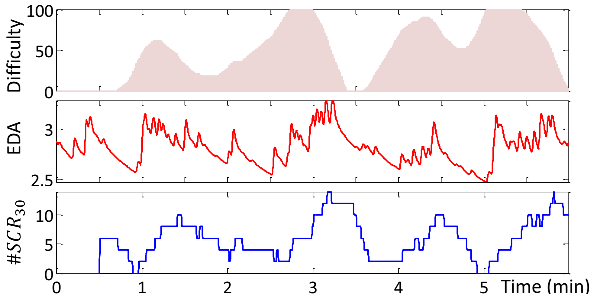

Fig. 6 Experimental results during the closed-loop phase 2 (subject P1; speed): (top) difficulty, (middle) raw EDA response, (bottom) average #SCRs over a 30-second window.

$\#SCR_{30}$ data in Fig. 5 over the range 0-100%. As shown in Table 1, the speed condition has the largest k_F, indicating that it is the most effective game mechanics, whereas weather is the least effective. Finally, 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, shown in Table 1, indicate that the speed mechanics also provides the fastest response (lowest rise time).

Finally, we performed a 2-way ANOVA, with game difficulty and game mechanics as main effects, and $\#SCR_{30}$ as the dependent variable. Both effects were statistically significant ($p = 1.75 \times 10^{-8}, 0.025$, respectively) and interact ($p = 0.716$). We also performed 1-way ANOVA to compare the three mechanics on the basis of rise times ($p = 0.0178$). Altogether, these results along with post-hoc tests indicate that the effects of game mechanics and difficulty levels are statistically significant, and that speed is the most effective mechanics in terms of modulating the player's arousal level.

C. *Experimental results: closed loop*

In closed-loop operation, the controller manipulates the game difficulty to maintain the player's arousal level around a setpoint, defined as the average $\#SCR_{30}$ from the open-loop phase. We use two metrics to evaluate the three game mechanics in a closed-loop configuration: (1) arousal ($\#SCR_{30}$), and (2) mean squared tracking error. From our earlier discussion (see section VI.A) a better game mechanics would result in lower tracking errors as well as fewer oscillations around the setpoint.

Statistics for $\#SCR_{30}$ under the three game mechanics are showed in Table 1. The speed mechanics has the largest $\#SCR_{30}$ as well as the lowest standard deviation (σ), whereas steering has the largest σ and weather has the lowest $\#SCR_{30}$. 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 ($p = 0.051$). Finally, we compared the tracking errors incurred by each mechanics in terms of mean squared error (MSE) between the setpoint and the player's $\#SCR_{30}$. As shown in Table 1, speed mechanics had the lowest error (averaged across subjects) when compared to the other two mechanics. However, a 1-way ANOVA shows that differences in MSE are not statistically significant ($p = 0.514$).

Table 1. Summary statistics from the experimental trials

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)

VII. Discussion and Future Work

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

To illustrate the model, we first performed simulation in open-loop and closed-loop configurations. Findings from these simulations were then corroborated experimentally through user studies. These results suggest that our model can be used to analyze the sensitivity of other gaming systems to their various components (e.g., controller, primary and secondary mechanics, physiological measures, etc.). As an example, a designer interested in some other physiological variable (e.g. EEG) may be able to incorporate the dynamics of EEG 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 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. [21] which 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 [22] studied the EDA 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 EDA. 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.

A. *Future work*

In our experimental protocol, participants played the game during a single session. This allowed us to estimate model parameters (k_F: game effectiveness; k_B: backward proportionality constant) once during the initial open-loop phase, and maintain them constant during the subsequent closed-loop phase. Additional work is required to test whether the model holds across multiple sessions. This may require that the parameters k_F and k_B be allowed to vary over time as the player becomes more proficient.

Additional work will test the model with other physiological markers. HRV is particularly appealing since it can be computed from heart rate monitors that can be worn inconspicuously and do not interfere with daily activities (e.g., grasping, typing). Arousal measures from EDA and HRV may also be combined for added robustness. As an example, Boucsein et al. [20] used a combination of NS.SCR and HRV to filter out motion artifacts. Since these variables change in opposite directions with increasing task demands (e.g. NS.SCR increases while HRV decreases) simultaneous increases in both variables can be dismissed as an indication of motion artifacts rather than of changing task demands.

In our study we used a proportional controller for modulating the game parameters. Adding integral and derivative terms (a PID controller) may, theoretically, further reduce the rise time, and decrease oscillations and settling time. The performance of other controller and their mappings with individual game mechanics and physiological parameter also needs to be studied. Future work may also explore simultaneous adaptation of multiple game mechanics. When combined with multimodal physiological sensing, the resulting multiple-input multiple-output (MIMO) system may provide additional degrees of freedom to model the complex human-game interaction.

Our methods may be used to design adaptive games that help the player achieve and maintain a state of flow [23]. Flow is defined as the cognitive state which leads to deep enjoyment; this is achieved by the right balance between the player's skill and difficulty of the activity. By tracking difficulty levels, player performance, arousal level and skill (i.e., through calibration), a control law may be used to dynamically maintain a proper balance between difficulty and skill level such that the player stays in flow. Our approach is also relevant to applications beyond entertainment. As an example, biofeedback games may be modified for teaching stress self-regulation. From a control-theoretic perspective, this would entail replacing the negative feedback loop with a positive feedback, such that the player is rewarded for staying calm and penalized for displaying high arousal. As a result, the player 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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