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ORIGINAL PAPER

A comparative study of game mechanics and control laws for an adaptive physiological game

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Abstract We present an adaptive biofeedback game that aims to maintain the player's arousal by modifying game difficulty in response to the player's physiological state, as measured with wearable sensors. Our approach models the interaction between human physiology and game difficulty during gameplay as a control problem, where game difficulty is the system input and player arousal its output. We validate the approach on a car-racing game with real-time adaptive game mechanics. Specifically, we use (1) car speed, road visibility, and steering jitter as three mechanisms to manipulate game difficulty, (2) electrodermal activity as physiological correlate of arousal, and (3) two types of control law: proportional (P) control, and proportional-integral-derivative (PID) control. We also propose quantitative measures to characterize the effectiveness of these game adaptations and controllers in manipulating the player's arousal. Experimental trials with 25 subjects in both open-loop (no feedback) and closed-loop (negative feedback) conditions show statistically significant differences in effectiveness among the three game mechanics and also between the two control laws. Specifically, manipulating car speed provides higher control of arousal levels than changing road visibility or vehicle steering. Our results also confirm that PID control leads to lower error and reduced oscillations in the closed-loop response compared to proportional-only control. Finally, we discuss the theoretical and practical implications of our approach.

Keywords Physiological games · Dynamic game balancing · Control theory

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1 Introduction

Physiological sensors have garnered a great deal of attention in the gaming research community [1–5]. Physiological variables such as heart rate (HR), skin conductivity, Electroencephalography (EEG) etc. 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 that leverage the broad appeal of videogames to improve patient compliance.

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 simultaneously 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 [7,8], 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). Sustained arousal at an optimal level is beneficial as it can lead to higher performance and reduced anxiety [5] and improved attention levels [9,10]. 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. Third, it provides objective measures of system performance (error, oscillation) that are complementary to subjective and observation-oriented measures often used in game evaluations. Implicit here is the assumption that there is a mapping between the psychophysiological variables [11,12] 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 EDA is controllable [7,8]. Finally, the approach is not limited to maintaining sustained arousal levels, and could be used to track time-varying arousal setpoints, e.g., oscillatory levels of arousal.

To validate our approach, we have developed an adaptive multimodal car-racing game (with unimodal feedback) and characterized three different game-adaptation mechanics: visibility, steering, and speed. Our evaluation consists of three 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 two different feedback control laws –proportional (P) control, and proportional-integral-derivative (PID) control, to maintain the player's arousal around a desired setpoint. Our results show that speed adaptation is more effective than the other two mechanics in both open-loop and closed-loop conditions as measured by the skin conductance response, rise time, and mean squared error, and that the PID controller can reduce tracking errors and dampen oscillations in EDA, as compared to P control.[1]

The rest of the paper is organized as follows. Section 2 summarizes prior work on integrating physiological sensors with videogames. Section 3 describes our modeling methodology based on control theory. Section 4 describes the adaptive videogame we have developed to validate our model, followed by the experimental protocol in Sect. 5. Section 6 presents results from simulation as well as user studies. Finally, Sect. 7 summarizes our findings and provides direction for future work.

[1] An earlier version of this work was presented at the International Conference on Affective Computing and Intelligent Interaction (ACII'13) [13].

2 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[2] [14]. 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 [15]. This is in agreement with Hook's affective loop theory, which argues for involving both mind and body as the basis for designing interactive affective systems [16], and Yannakakis studies on affective physical interaction [17]. 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 what has been described as a biocybernetic loop [18,19].

Rani et al. [5] 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 physiological indicators) caused 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: better performance led 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. 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. [20] 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 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 and discovered significant increases of immersion only in the explicit biofeedback condition [20]. In a related study, Nacke et al. [2] investigated sensor mappings 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)

[2] 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.

control would be to use HR or skin conductivity. The authors concluded 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 [9,10] 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. In a classical study by Pope et al. [19] participants were asked to perform a tracking task analogous to those performed by crew-members in flight management. When the adaptive automation was run in a negative feedback loop, 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. [21,22] 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 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. [3] 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. [23] 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. [24] 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., [25]. 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. [26] 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. Towards this aim, in recent work [27] we presented a biofeedback game that teaches relaxation skills by monitoring the breathing rate of the player. Namely, we used a positive feedback loop to penalize fast breathing by increasing the randomness of the game. Physiological measurements showed that practicing the game leads to lower arousal during a subsequent stress-inducing task.

3 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. 1a, the basic building blocks of a control system are (1) the plant or system we wish to control, (2) a sensor, which measures the state of the plant, and (3) 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 heating/cooling system, the controller is the thermostat, and the sensor is a thermistor (typically 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 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).

Figure 1b shows the generic block diagram when applied to a multimodal adaptive physiological game. In this case, the player is the "plant" whose output (arousal) we seek to main-

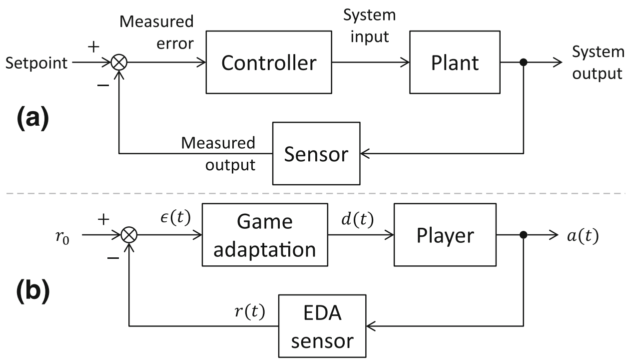

Fig. 1 Block diagram of **a** a classical feedback control system, and **b** our adaptive physiological game

tain constant around a setpoint. The sensor in the feedback loop is a physiological sensor, which converts the player's arousal into a measurable variable –EDA in our case; see Sect. 4.2. Finally, the game-adaptation engine takes the deviation between the desired and the measured arousal levels and modulates the game parameters to reduce the error between both. 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 [18,28].

The block diagram in Fig. 1b is an example of a feedback system with a human in the loop. Although there is no well-defined transfer function for the human [29], 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 model:

$$r(t) = r(t-1) + k_F d(t) \quad (1)$$

$$d(t) = d(t-1) - k_P \epsilon(t) \quad (2)$$

$$\epsilon(t) = r_0 - r(t) \quad (3)$$

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[3] 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 a particular game mechanics in shaping the player's arousal level (larger values of k_F being better). Equation (2) is the proportional (P) controller model; the larger the error (difference between the setpoint and desired arousal) the larger the change in difficulty level, with the backward proportionality constant k_P controlling how quickly the game difficulty will change. Large values of k_P can reduce steady state errors quickly, but can also result in large oscillations and even instability [19].

The performance of the proportional controller in Eq. (2) can be improved by incorporating derivative (D) and integral (I) terms, which results in the PID controller model that is widely used in industrial control applications [7,8]:

$$d(t) = d(t-1) - \left(k_P \epsilon(t) + k_D \frac{d}{dt}\epsilon(t) + k_I \int \epsilon(t)dt\right. \quad (4)$$

This controller consists of three coefficients: a proportional gain k_P, an integral gain k_I, and a derivative gain k_D. The proportional gain k_P has the same effect as the backward proportionality constant in the P controller. The integral gain k_I accumulates the system error and takes action to accelerate the movement of the process towards the setpoint and reduce error, at the expense of increasing system oscillations. The derivative gain k_D measures the instantaneous slope of the error, predicts the overshoot and takes corrective measures to reduce system oscillations. Table 1 summarizes the effects of the individual terms on system performance.

Table 1 Effect of increasing controller gains on system performance

	Rise time	Steady-state error	Oscillations
k_P	Decrease	Decrease	Increase
k_I	Decrease	Decrease	Increase
k_D	Minor effect	No effect	Decrease

4 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/puzzles, role playing, action/adventure, sports, racing, shooter, fighter, arcade) [30] 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 [31] to incorporate physiological feedback from an EDA sensor –see Fig. 2b. To provide consistency across experimental conditions, 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

[3] As we will see in Sect. 4.2, we use the number of skin conductance responses (SCRs) as the measure of EDA.

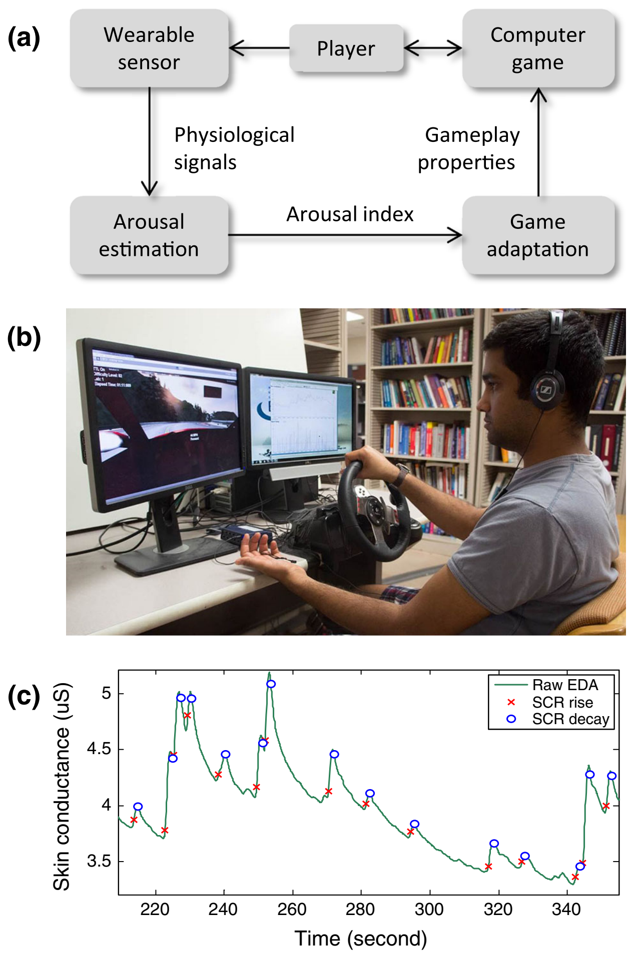

Fig. 2 **a** Block diagram of the adaptive physiological game. **b** A participant playing the car-racing game. **c** Recording of electrodermal activity (EDA) and detected SCR events

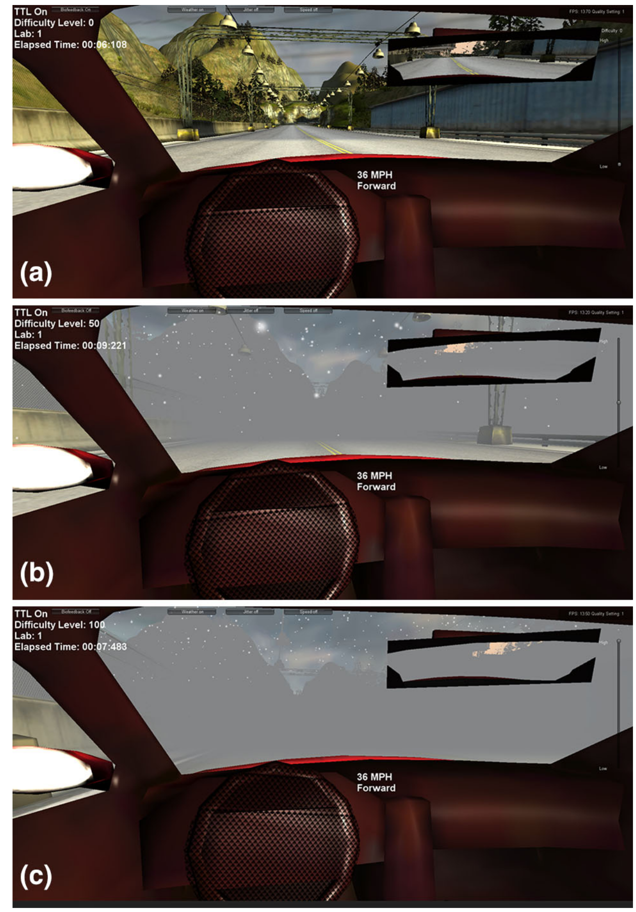

Fig. 3 Effect of inclement weather (IW) on road visibility. **a** Under 0 % IW, visibility is perfect. Visibility drops to 10 and 2m under **b** 50 % and **c** 100 % IW, respectively

by recording 10 game plays of a proficient player during a pilot study.

4.1 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; see Fig. 3. 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 nose. At 0 % disturbance, no noise was added to the steering signal. At 50 % disturbance, an angular jolt of 45° was added to the player's intended steering direction; at 100 % disturbance, an angular jolt of 90° 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 s. 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 (a factor of 1). 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 half the nominal speed at that location i.e., 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.

4.2 Physiological measure of arousal

We estimated the players' arousal through their electrodermal activity (EDA). EDA is known to be a linear correlate to arousal and consists of two basic components, (1) a slowly changing offset known as the skin conductance level (SCL), and (2) a series of transient peaks known as skin conductance responses (SCR) [32] that occur in response to stimulus including startle events (i.e., an unexpected loud noise), cognitive activity, emotional arousal, and even body movements but also spontaneously, in which case they are referred to as non-specific (NS.SCR) [33]. 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. For these reasons, we used the number of SCRs within a time window (T = 30 s) sliding by 1 s as a measure of arousal. This window size was chosen as a tradeoff between responsivity of shorter windows and the smoothness of longer windows, and has been recommended in prior studies to obtain reliable estimates of arousal. Figure 2c 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.

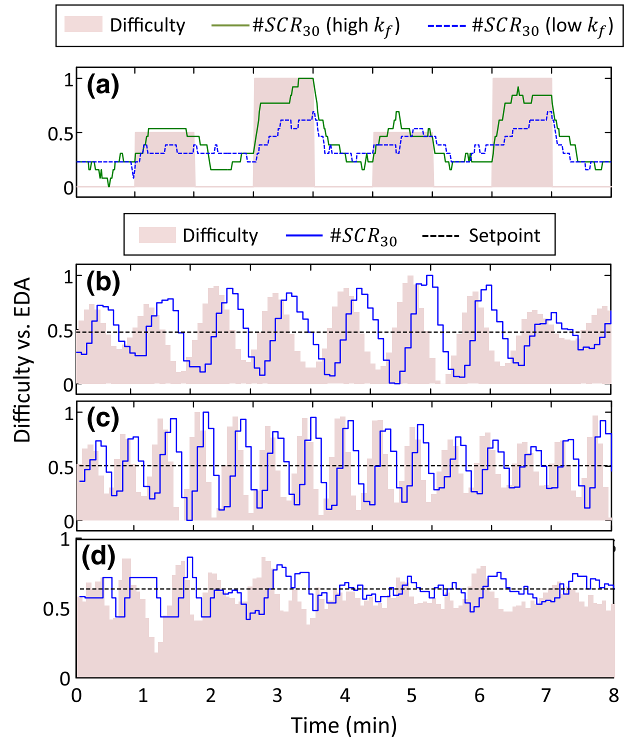

Fig. 4 **a** Open loop simulation for high vs. low game effectiveness (high $k_F = 0.9$; low $k_F = 0.5$). **b** Closed loop simulation for slow difficulty change (low $k_P = 0.1$; $k_F = 0.9$). **c** Closed-loop simulation for fast difficulty change (high $k_P = 0.9$; $k_F = 0.9$). **d** Closed-loop simulation for the PID controller ($k_P = 1.11$, $k_I = 0.05$, $k_D = 4.86$)

5 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-five students (age 18–33 years) participated in the study. Of these, 20 participants evaluated the P-control adaptation: 7 for weather, 6 for steering and 7 for speed. The remaining 5 subjects evaluated the PID-control adaptation for speed. The majority of participants (>60 %) had little to no experience with car racing and other console games.

We received approval from the Institutional Review Board prior to the study, and signed consent from each individual participant before the session. Participants played the game on a 22" LCD using a Logitech G27 racing wheel [34]; see Fig. 2b. 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.) [35] 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 [36]. To avoid motion/pressure artifacts, participants were instructed to use only the dominant hand to control the steering wheel.

The experiments were conducted in three phases on the same day: training (phase 0), open loop (phase 1) and closed loop (phase 2). During phase 0, biofeedback was disabled and participants drove the car for one lap around the circuit to familiarize themselves with the game and the controls.

During the open-loop phase (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 phase 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-s window ($\#SCR_{30}$) across difficulty levels, and used it as the target setpoint for the closed-loop experiments. Since the open-loop experiment contains an unequal number of blocks (5 blocks at 0 % difficulty, 2 at 50 %, 2 at 100 %; see Fig. 4a), the resulting setpoint is biased towards low difficulty (33 %).

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 proportional control law in Eq. (2) or the PID control law in Eq. (4). Phase 2 allowed us to evaluate the effectiveness of the feedback loop in maintaining the player's arousal level at the desired value.

6 Results

6.1 Simulation results

First, we illustrate the behavior of the system by simulating the model in Eqs. (1–4). Results for phase 1 (open loop) are shown in Fig. 4a for two values of k_F (low, high). Here, the game difficulty level was driven by the step sequence {0, 50, 0, 100, 0, 50, 0, 100, 0} %. For high k_F(=0.9), 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(=0.5) 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.

Closed-loop results (phase 2) for the P controller with low and high values of the proportional gain k_P and high forward gain k_F are shown in Fig. 4b–c. High value of k_P lead to larger changes in game difficulty in response to the player's arousal, which in turn leads to large oscillations in arousal and game difficulty. In contrast, low values of k_P lead to fewer oscillations, which are likely to be more desirable to the player, at the expense of increasing rise time, which reduces the responsiveness of the system during gameplay (an undesirable effect).

To address the issue of oscillations while maintaining responsiveness (low rise time), we then evaluated a PID controller in Eq. (4), which includes derivative and integral terms. The derivative term measures the instantaneous slope of the error and dampens the response if the controlled variable is oscillating rapidly. In contrast, the integral term measures the accumulated error and eliminates the residual steady state error. PID parameters (k_P, k_I, k_D) were optimized using the Zielger Nichols method [37], as described in the Appendix. The PID simulation results are shown in Fig. 4d. Comparing those against the P controller response in Fig. 4b–c, we observe that the PID controller is able to significantly dampen the oscillations in the system response.

6.2 Experimental results: open loop

Figure 5 shows experimental results for one subject during phase 1 (open loop) under the speed-adaptation condition; similar results (not shown) were observed for other subjects in the study. Arousal, as measured by the $\#SCR_{30}$ index, closely follows the step input in game difficulty and increases in proportion to the magnitude of the change in difficulty. These results are consistent with those in the simulation study

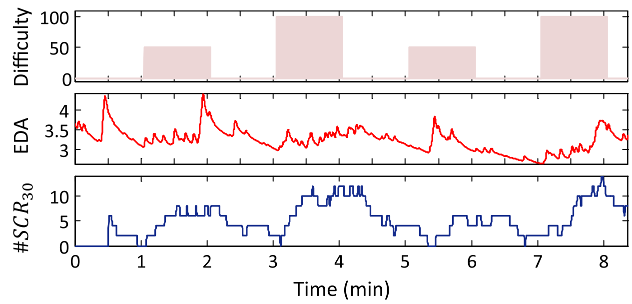

Fig. 5 Experimental results during the open-loop phase 1 (speed) for one subject: (*top*) difficulty, (*middle*) raw EDA response, (*bottom*) average #SCRs over a 30-s sliding window

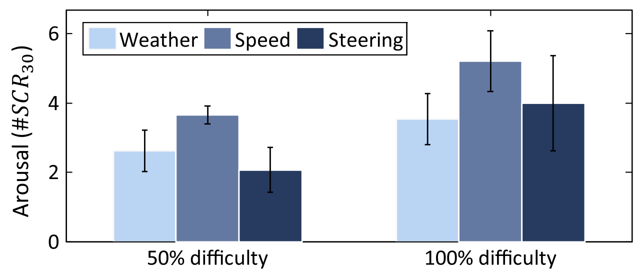

Fig. 6 Average SCR across all subjects during open-loop for the three game mechanics at 50 and 100 % difficulty level (normalized by subtracting baseline SCR at 0 % difficulty level)

of Fig. 4a, which suggests that Eqs. (1–4) may be a valid model of the interplay between arousal and difficulty.

Next, we compared 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. Figure 6 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 adaptation is the most effective of the three mechanics. However, whereas steering shows a linear increase in $\#SCR_{30}$ when going from 50 to 100 %, the other two mechanics show saturation effects. This suggests that there is a non-linear relationship between the difficulty level in our percentage-scale and the player's arousal. 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 diffi-

Table 2 Summary statistics from the experimental trials comparing the three game mechanics (weather, speed, and steering) with the proportional control law

Condition	Open-loop phase		Closed-loop phase	
	k_F (RMSE)	Rise time (SD) in seconds	Average #SCRs (SD)	Mean squared error (SD)
Weather	1.76 (0.69)	38.8 (18.8)	3.22 (0.59)	2.92 (1.70)
Speed	**2.6 (0.86)**	**35.5** (11.3)	**4.6** (0.41)	**2.75** (1.46)
Steering	1.99 (0.06)	40.3 (13.3)	3.8 (1.14)	2.91 (1.75)

Bold values indicate that the variable (speed) is significantly different from the other variables (weather and steering) in terms of the measured quantities

culty); 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, as measured by the parameter k_F in Eq. (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 %. Speed adaptation 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 2, indicate that the speed mechanics also provides the fastest response (lowest rise time).

To assess the statistical significance of the results, 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 $F(2, 45) = 3.96$, $p < 0.05$ and $F(2, 45) = 26.5$, $p < 0.05$, respectively; the interaction between effects was not significant [$F(4, 45) = 0.53$, $p > 0.05$]. To compare the three difficulty levels (0, 50, and 100 %) in their ability to elicit NS.SCRs, we performed repeated measures 1-way ANOVA (individually for each of the three game mechanics). The ANOVA statistics indicate a statistically significant difference among the three difficulty levels for speed [$F(5, 10) = 5.67$, $p < 0.05$] and steering $F(5, 10) = 3.43$, $p < 0.05$), but not for weather $F(5, 10) = 2.72$, $p > 0.05$. We also performed 1-way ANOVA to compare the three mechanics on the basis of rise times; $F(2, 15) = 4.75$, $p < 0.05$. Altogether, these results 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 arousal level of the player.

To assess inter-participant variability in NS.SCR trends over the three difficulty levels, we performed Kendall's τ rank correlation test. Kendall's τ is a non-parametric measure of the strength of monotonic associations between two variables. For speed and steering mechanics, we obtained $\tau = 1$ for all but one participant with respect to all other participants. This indicates that the NS.SCR response followed the trend $SCR_{0\,\%} < SCR_{50\,\%} < SCR_{100\,\%}$ for all but one participant in both conditions. In the case of weather mechanics the results were mixed with for 4 out of 6 participants following this trend.

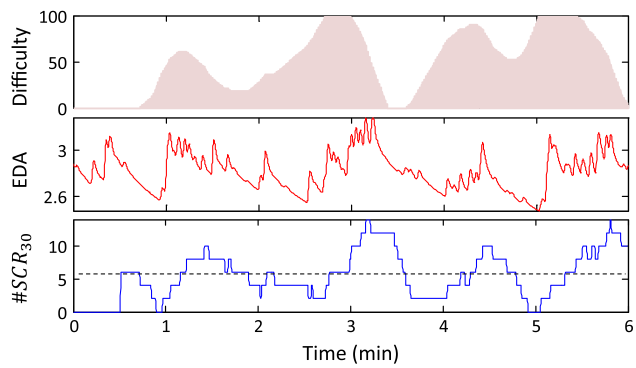

Fig. 7 Experimental results for the proportional controller during the closed-loop phase 2 (speed) for one subject: (*top*) difficulty, (*middle*) raw EDA response, (*bottom*) average #SCRs over a 30-s sliding window with the target setpoint (*dotted line*)

6.3 Experimental results: comparison of game mechanics under proportional control (closed loop)

In closed-loop operation, the P 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. Figure 7 shows the closed loop response (game difficulty level, raw EDA, and $\#SCR_{30}$) for one subject playing the game under the speed mechanics controlled by the proportional controller. As the arousal of the player goes below (above) the target setpoint, the proportional controller drives the game difficulty higher (lower) so as to elicit the desired response.

We used two metrics to evaluate the three game mechanics in the closed-loop configuration: (1) arousal ($\#SCR_{30}$), and (2) mean squared tracking error. From our earlier discussion (see Sect. 4.1) a better game mechanics would result in lower tracking errors as well as fewer oscillations around

Table 3 Significance results (t test) for the three game mechanics in open-loop and closed-loop configurations (*$p < 0.05$)

Condition	Open-loop	Closed-loop	
	Rise time	Average #SCRs	Mean squared error
Speed – Weather	t(5) = 2.51*	t(5) = 2.89*	t(5) = 3.69*
Speed – Steering	t(5) = 3.67*	t(5) = 2.14*	t(5) = 0.76
Steering – Weather	t(5) = 1.82	t(5) = 0.61	t(5) = 0.64

Table 4 Summary statistics from the experimental trials comparing proportional (P) and PID control of speed adaptation

Control law	Average #SCRs (SD)	Mean squared error (SD)	Oscillations (SD)
PID	**4.64** (0.56)	**2.61** (1.53)	**5.25** (3.09)
P	4.6 (0.41)	2.75 (1.46)	7.5 (2.57)

Bold values indicate that the particular control law (PID) is improves the system performance when compared to the other control law (P) in terms of the measured quantities

the setpoint. Statistics for $\#SCR_{30}$ under the three game mechanics are shown in Table 2. 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; $F(2, 15) = 3.47,\ p > 0.05$. Finally, we compared the tracking errors incurred by each controller in terms of root mean squared error (MSE) between the setpoint and the $\#SCR_{30}$ elicited from the player. As shown in Table 2, the speed mechanics had the lowest error (averaged across subjects) when compared to the other two game mechanics. However, a 1-way ANOVA shows that differences in MSE are not statistically significant; $F(2, 15) = 1.05,\ p > 0.05$.

We also performed pairwise t-tests to compare the three game mechanics in both open-loop and closed-loop configurations; results are summarized in Table 3. The t-test statistics indicate that the speed mechanics is significantly different from the weather mechanics in both open-loop and closed-loop configurations. When comparing speed with steering jitter, the differences were significant for rise time and average # SCRs, but not for MSE. We did not observe statistically significant differences between the steering and weather conditions. These statistical results corroborate the results discussed earlier (Table 2).

6.4 Experimental results: comparison of P and PID controllers under speed game mechanics (closed loop)

In the fourth and final experiment, we tested whether the simulation results with a PID control law (see Sect. 6.1) would also hold experimentally. As before, we tuned the PID gains (k_P, k_I, k_D) with the Zielger Nichols method [37]–refer to the Appendix section. Figure 8 shows the closed-loop

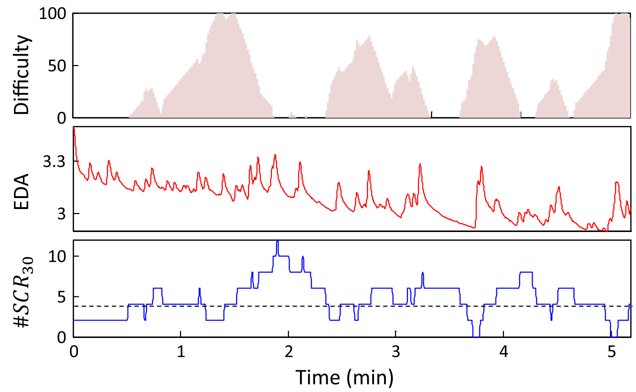

Fig. 8 Experimental results for the PID controller during the closed-loop phase 2 (speed) for one subject: (*top*) difficulty, (*middle*) raw EDA response, (*bottom*) average #SCRs over a 30-s sliding window with the target setpoint (*dotted line*)

response for one subject playing the game under PID control of speed adaptation. Visual inspection of these results indicates that, compared to those under proportional control–see Fig. 8 system oscillations around the setpoint are dampened and the error is reduced.

In a final step, we quantitatively compared the performance of the P and PID control laws for game adaptation. For this purpose, we used car speed as the game mechanics because of its better performance on the closed-loop experiments in Sect. 6.4. As before, we used arousal ($\#SCR_{30}$) and tracking errors (MSE) as performance metrics, but also included the number of oscillations, measured as the number of zero-crossings at the target setpoint in the $\#SCR_{30}$ response. Summary statistics are shown in Table 4. We performed 1-way ANOVA analysis with controller type (P, PID) as the factor and performance ($\#SCR_{30}$, MSE, oscillations) as the dependent variables. In the case of $\#SCR_{30}$, differences between the two controllers were not statistically significant $F(1, 8) = 1.02, p > 0.05$; this result is to be expected since both controllers used the same adaptation mechanism (speed). Comparison of the tracking errors (MSE), however, shows a marginally significant difference in favor of the PID controller $F(1, 8) = 4.42,\ p > 0.05$. Finally, PID controller had fewer oscillations than the P controller, and this difference was statistically significant $F(1, 8) = 5.4,\ p < 0.05$. These results are consistent with our simulation studies (Sect. 6.4) and corroborate the theoretical predictions of Table 1.

7 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 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 studies in open-loop and closed-loop configurations. Findings from these simulations were then corroborated experimentally through user studies. These results suggest that the model in Eqs. (1–4) can 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 some other physiological variable (e.g. EEG) may be able to incorporate the dynamic properties of EEG into the model, study its effects, and design a suitable controller.

During the design stage, we considered a number of game mechanics including traction properties of the road/car, aggressiveness of a competitor car (enemy AI), lag in controls, and the visual appeal of the scenery. We chose weather as an example of an 'ambient' modification that would directly affect performance (i.e., by reducing visibility). In contrast, steering jitter is an example of a disturbance that induces frustration/loss of control, whereas speed is an example of an intuitive manipulation. We chose these three game mechanics for comparison because of their different impact on gameplay and affective experience. 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 shortest 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. [38] 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 [39] 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.

While it is reasonable to assume that the relationship between difficulty and arousal is monotonic, its particular shape (e.g., linear, power, sigmoidal) depends largely on the arousal measure being used, the game mechanics being adapted, and the scale (i.e., logarithmic) of the parameters. For simplicity, in Eq. (1) we assumed the two variables to be linearly related. However, as discussed in Sect. 4.2, whereas steering does show a linear increase in $\#SCR_{30}$ when going from 50 to 100 % difficulty, the other two mechanics show saturation effects. This suggests that there is a non-linear relationship between the difficulty level in our percentage-scale and the player's arousal.

7.1 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_P: 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. Similar strategies have been suggested by Yannakakis et al. [17] to evolve games over time with players' increasing proficiency/experience. Similarly, we used the same gains (k_P, k_I, k_D) for all the participants playing the game with the PID controller. To account for player differences and for the expected improvement in performance over time we would need to recalibrate the gain values from the calibration phase individually/separately for each participant. Our method was validated on a relatively small sample size (25 participants). Extensive/longitudinal trials would be required ascertain its statistical significance, and clinical validity and reliability.

Collisions between the player's car and objects on the shoulder of the track (i.e., guard rails, traffic signs) can occur during gameplay. In the event of a collision, the player must bring the car back on the track and resume driving. Collisions can lead to startle or orienting responses, with the corresponding spike in skin conductance (i.e., an SCR). This in turn causes the biofeedback control loop to reduce game difficulty, allowing the player to get back on the track. While at present we don't track collision events explicitly, this information may be used to extract complementary information from the EDA response, such as the latency or amplitude of SCRs during startle or orienting responses. As an example, declining SCR amplitudes with successive collisions may be used as a measure of habituation.

To better quantify the players' emotional experiences during gameplay, additional physiological signals may be considered, such as heart rate variability (HRV) and breathing rate. As suggested by Mandryk et al. [40], these physiological signals can be transformed into arousal and valence and mapped into emotional states relevant to video gameplay (e.g. boredom, excitement, challenge, fun, frustration etc.). HRV is particularly appealing since it can be computed from HR monitors, which are low cost, can be worn inconspicuously and, unlike EDA sensors, do not interfere with normal activities (e.g., grasping, typing). Arousal measures from EDA and HRV may also be combined for added robustness. As an example, Boucsein et al. [21] 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 proportional and PID controllers for modulating the game parameters. Adding the integral and derivative terms led to reduction in the error and oscillations. The performance of other controller and their mappings with individual game mechanics and physiological parameter also needs to be studied. As an example, a reinforcement-learning controller may learn a mapping between arousal level and game difficulty and the optimal setpoint during gameplay.

Our methods may be used to design adaptive games that help the player achieve and maintain a state of flow [41]. 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 [41]. 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 games. As an example, biofeedback games may be modified for teaching stress self-regulation. From a control-theoretic perspective, this would entail a simple modification: 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.

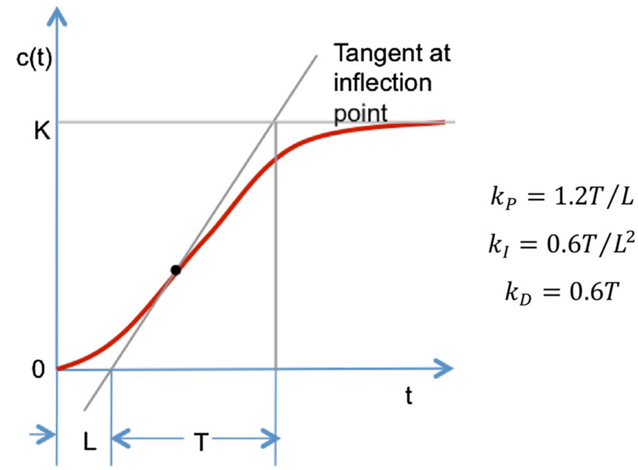

Fig. 9 Ziegler Nichols method for tuning a PID controller. Here, $c(t)$ is the unit step response and K is its steady state value

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8 Appendix

The Zielger Nichols method [37] provides plug-in formulas for the PID gains by considering the unit-step input response of the system. The unit step response generally follows an S-shaped curve characterized by two parameters: the delay time (L) and the time constant (T); see Fig. 9. Both parameters are obtained by drawing a tangent line at the inflection point of the unit-step response and determining the intersection of the tangent with the axes. Once these parameters (L and T), have been obtained, the PID gains can then be computed via the plug-in expressions in Fig. 9. For our experiments, we used the transition from 0 to 100 % difficulty in the open loop phase as a unit step input. This gives rise to the S-shaped NS.SCR response from which L/T and the PID gains are estimated. Calculation according to see Fig. 9 leads to the following PID gains: $k_P = 1.115$; $k_I = 0.05$; $k_D = 4.861$. These parameter settings were computed on the open-loop experimental data in Sect. 4.2, and used both for the closed-loop simulations and closed-loop experiments.

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