A Fuzzy Control System for Inductive Video Games

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Abstract—It has been shown that the emotional state of students has an important relationship with learning; for instance, engaged concentration is positively correlated with learning. This paper proposes the Inductive Control (IC) for educational games. Unlike conventional approaches that only modify the game level, the proposed technique also induces emotions in the player for supporting the learning process. This paper explores a fuzzy system that analyzes the players’ performance and their emotional state for controlling the level and aesthetic content of an educational video game. The emotional state of the player is recognized through voice analysis. A total of 20 subjects played a video game designed to practice basic math skills; for each trial, a student plays two times in a row the same game but each time the game was controlled by one of the two approaches —Dynamic Difficulty Adjustment (DDA) and IC, the playing order was assigned randomly. Results show that when the proposed approach is used the participants changed faster from Unpleasant–low to pleasant or high emotions, and reached softly and kept in the flow zone. These experiments demonstrate that the inductive control technique improves the learning effectiveness through detection and stimulation of positive emotions.

Index Terms—Fuzzy control, Affective computing, Interactive learning control

1 INTRODUCTION

An educational video game is a computer game that induces user engagement while promoting cognitive learning and social skills. Several authors have suggested the potential of video and computer games as educational tools [1]: for example, Rosas et al. [2] show that learning through video games has positive effects for children in the first years of school. Indeed, under certain conditions, educational games are preferable over other teaching methodologies Peterson [3].

In general, a successful educational game requires that its mechanics (e.g., the player’s experience) and aesthetics (environment shapes, animations, sound, etc.) fulfill the expectations of the target population. Each player has specific characteristics such as preferences, abilities, emotions, etc., therefore, the game must change its dynamics and aesthetics.

Adaptive Game Adjustment (AGA) is a common approach to optimize output performance measures of the game (e.g., the player’s experience). The AGA methods can be divided into two general classes [4]:

Dynamic Difficulty Adjustment (DDA). These methods (aka dynamic game balancing) automatically change parameters, scenarios, and behaviors in a video game in real-time, based on the player’s ability. In the context of serious games, these methods use the Zone of Proximal Development theory (ZPD) [5]. In his theory, Vygotsky considers two development levels for learners: the actual development level—what a learner can do on her own—and the potential development level—what a learner can perform with some assistance. Vygotsky defines the ZPD as:

“The distance between the actual development level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or collaboration of more capable peers.”

A simple interpretation of the ZPD theory is that the instructional material should not be too difficult or easy for the learner [6]. This approach argues that by keeping learners in their ZPD, negative emotional extremes can be prevented—e.g., being bored, confused or frustrated [6]. Likewise, the Flow theory [7, 8, 9] describes different mental states that can be induced in a learner by a combination of skill and challenge levels. The ‘flow experience’ model marks an achieved balance of arousal-increasing and arousal-decreasing processes. The flow model describes this balance in terms of the fit between perceived challenges and skills: an activity wherein skills predominate reduces arousal; an activity wherein challenges predominate increases arousal; an activity wherein skills predominate reduces arousal. Thus, a synchrony of challenges and skills permits a state of deep involvement, while the pitfalls of either over- or under-arousal (i.e., anxiety or boredom) are avoided.

Emotionally Adaptive (EA) Methods. These methods consider that by maintaining a high level of engagement, the game experience could lead to psychological benefits, such as a sense of efficacy and power over one’s environment, as well as improvements in learning [10]. The Affective Loop [11, 12] states that: by providing the right game content the game influences the player’s experience, and by detecting the emotional state of the player the game can adapt its content.

Anxiety and boredom emotions have a negative effect
in learning [13], it has been found that boredom is the most persistent emotion in educative video games and it is was associated with poorer learning and problem behaviors. Anxiety impact negatively on learning, especially on Math learning [14]. Math anxiety is a feeling of tension, worry, and fear in situations involving math-related tasks [15], e.g. the tasks of the math fractions game used in this article. In the study of [14] with undergraduate students present a negative correlation, Math anxiety was negatively related with math performance, whereas math motivation positively associated with math performance.

The main contribution of this paper is the Inductive Control (IC) for educational games. The proposed technique uses the estimated emotional player’s state to induce emotions for supporting the learning process; that is, the IC approach considers that better learning results can be obtained by inducing desirable emotions to students through the control of both the level and aesthetics of the game.

The overview of the proposed approach is shown in Fig. 1, the video game can obtain the player’s emotional information and performance (score) as the player (student) interacts with it. IC requires to known the users’ emotional state for selecting the best aesthetic and difficulty level. To this end, an emotional detector from voice is used to estimate the players’ emotional state –expressed by arousal and valence. A fuzzy controller analyzes the score obtained by the player and the aesthetics in the previous stage, and the current player’s arousal and valence to generate the new difficulty level and aesthetics for the next stage. We believe that some multimedia content can: (i) alleviate some negative emotional states that are common in the constructive learning process (e.g., frustration), (ii) activate students that are in states that prevent learning (e.g., boredom or tiredness), and (iii) keep students in states that favor learning (e.g., happiness). The rules included in the fuzzy control consider many of these cases, they also take advantage of the knowledge of what aesthetic content was previously used. This could be vital to avoid unlearning states for long periods; e.g. it is worthwhile to use unpleasant sounds to stimulate a bored student that cannot be activated by using harder difficulty level nor using pleasant sounds.

Fig. 1. Overview of the proposed approach (IC).

The rest of this paper, is organized as follows: Section 2 reviews some concepts on emotions and how to identifying them, Section 3 describes relevant work of adaptive games, Section 4 introduces the proposed approach, Section 5 describes the method used in the empirical study, Section 6 presents and discusses the results, and Section 7 provides some conclusions together with perspectives for future work.

2 Identifying Emotions

Emotions can be defined as biologically based action dispositions that have an important role in the determination of behavior [17]. Emotions are complex events, Russell [16] considers that at the heart of an emotionally charged event there are states experiences simply feeling good or bad (valence), energized or enervated (arousal). The combination of these two dimensions is what Russell called the core affect [18]. The circumplex model [19] suggests that emotions can be distributed in a two-dimensional space (aka arousal-valence space), where a pleasant-unpleasant value is represented by the horizontal axis and high-low arousal is represented by the vertical axis (Fig. 2).

Emotions can be observed in facial expressions, gestures, body movements, as well as in voice. Besides these directly observable expressive channels, physiological changes can also occur in parameters such as blood pressure, heart rate, or electro-dermal activity that are not directly recognized by human observers [19].

In this paper, the emotional state of the player is recognized through voice analysis. This choice was made in order to take advantage of a non-intrusive, directly observable channel, that does not require additional sensors. In fact, recognizing emotion in voice has been successfully used in many applications; e.g., call centers [20], and human robotic interaction [21], among others.

Anagnostopoulos et al. [22] present a brief overview of classifiers in voice-based emotion recognition. A common approach for voice-based emotion recognition uses Hidden Markov Models (HMMs); for instance, the approach proposed by Schuller et al. [23] shows a high performance in recognition of seven discrete emotions (exceeding 86% recognition rate).

3 Related Work

The Experience-Driven Procedural Content Generation framework (EDPCG) [24] views the game content as building...
blocks of games, and games as potentiatiors of player experience. It states that to elicit player experience, one needs to assess the quality of the generated content (linked to the experiences of the player), search through the available content, and generate content that optimizes the experience for the player.

In this sense, the proposed approach applies the EDPCG framework to educational video games by using objective (arousal-valence) and game-play based (score ratio) player models and theory–driven content quality, with exhaustive content selector.

Some works focus on a specific emotional feature; e.g., the mental work load [25], the anxiety level [26, 27], or the arousal [28].

There are many studies that focus on providing instructional objects at the correct level of difficulty for the student. A common approach consists of planning the curriculum sequence, i.e. providing the student with the most suitable sequence of knowledge units and learning tasks (examples, questions, problems, etc.) [29]. This approach solves the problem of finding an optimal path through the learning material. IC, proposed in this paper can be easily adapted to these instructional objects because it finds the correct level of difficulty, but it also makes decisions based on the perceived student emotions.

Few studies have investigated how to improve the game–based learning performance by adapting the instructional material according to the learner’s current developmental and individual particularities; e.g., the way of thinking, feeling, behaving, and relating to others. For instance, some approaches [30, 31] identify the learning style for providing personalized learning materials –learning styles group common ways that people learn [32]– these methods use self-reporting or can analyze the physiological responses to know the user emotional state. In this sense, the proposed approach adopts the circumplex model for representing emotions; hence, both the game content and the user state can be modeled in the same way.

Liu et al. [27] analyze physiological signals to infer the the player’s probable anxiety and the game difficulty level is automatically adjusted in real time by using a finite state machine.

The proposed method relies on a fuzzy logic control. Fuzzy logic mimics human control logic in that it uses an imprecise but descriptive language to deal with input data, much like a human operator. In this sense, a closely related work by Hsieh and Wang [33], proposes a fuzzy approach for adapting opponents tactics to the behavior of the player such that the players win/loss rate is kept at their desired rate. That is, it only focuses on the difficulty level.

Finally, fuzzy logic has also been used to quantify emotion during play using physiological data. For instance, Mandryk and Atkins [34] use a fuzzy logic model to transform physiological signals –galvanic skin response (GSR), electrocardiography (EKG), electromyography of the face (EMG), and Heart Rate (HR)– into arousal and valence. A second fuzzy logic model is then used to transform arousal and valence into five emotional states relevant to computer game play: boredom, challenge, excitement, frustration, and fun. It demonstrates that the fuzzy logic models can be used to analyze emotions. The IC approach considers that it already has an emotion detector, and instead it focuses on how to promote a better learning scenario.

In conclusion, the novel approach proposed in this paper can be valuable in many contexts to improve the interaction between the student and the learning material.

4 Inductive Control

The proposed IC relies on a fuzzy logic control. Both the aesthetic content and the emotional state are represented by Russell’s circumplex model. As shown in Fig. 1 the inputs for the fuzzy control are: \( S \in [0, 1] \), the Score Ratio obtained by the player in the previous stage; \( \{V, A\} \), the current player’s emotional state; and \( \{V_{k-1}, A_{k-1}\} \), the nominal emotion induced by the aesthetics used in the previous stage, where \( V \) is the valence and \( A \) is the arousal. The outputs of the fuzzy control are: \( F \), the factor of difficulty level change and \( \{V_k, A_k\} \), the expected emotion induced by the aesthetic in stage \( k \). Factor \( F \) is used to select the new difficulty level \( D_k \) from the previous one \( D_{k-1} \); that is,

\[
D_k = F \cdot D_{k-1}.
\]

4.1 Membership functions

The control function designed for IC takes as input variables Valence and Arousal at different stages; we need to define the linguistic terms those variables can take on. Along with each linguistic term, we need to define their membership functions. Although most of the work that deals with fuzzy inference and control use an odd number of linguistic terms, that is not a requirement. The variables we use in performing fuzzy inference are defined with 2, 3, 4, or 5 linguistic terms; the number of them and their labels were taken from the application domain [35]. Henceforth, membership functions for arousal are labeled as LOW, MEDIUM, HIGH.

Another important design decision about the fuzzy inference system is the shape of the membership functions for the linguistic terms of the involved variables. Gaussian functions were chosen to represent fuzzy set membership. That representation conveys two main advantages: First, since they are continuous functions, the inferred membership levels of the output variables tend to be continuous, which was not the case for triangular membership functions. Second, those functions need less parameters in their specification (i.e., \( \mu \) and \( \sigma \)), while triangular functions need three and trapezoidal functions need four. Figures [5] and [6] show the linguistic terms associated to variables in the process and
their corresponding membership functions. For instance, Fig. 4(a) shows two membership functions for the player’s valence in the previous stage, \( V \in [-1, 1] \). Both functions have the same standard deviation (0.5), but the unpleasant function is centered at \( V = -1 \), while the pleasant function is at \( V = 1 \).

### 4.2 Fuzzy Rules

The fuzzy rules for the difficulty factor, shown in Table 1 follow the ZPD theory [3]. To induce emotions in the player, the current implementation only change sounds — but the results can be generalized to other aesthetics. For this aim, we use the IADS-2 International Affective Digitized Sounds [36]. The IADS was developed to provide a set of normative emotional stimuli for experimental investigations of emotion and attention.

Although it would seem that sounds should be capable of inducing a range of emotive states than these labels imply, the IC uses them as reference and it changes them in cases where the sound could not induce the required emotion. The fuzzy rules for aesthetics, shown in Table 2 were selected by applying the following theories and facts:

1) Russell [18] asserts that the emotional state is a biological product of evolution and therefore it likely has a function. Russell suggests a general principle of congruence: pleasant states facilitate attention to positive material (and vice-versa). For instance, feeling enthused gives a person a sense of optimism in choosing goals and plans. One might therefore choose a more difficult task and might work harder at what goal is chosen [18]. In this sense, the proposed rules have much more outputs with aesthetics that induce positive emotions than those that induce negative emotions.

2) Pleasant-high emotions are associated to engaged concentration which is positively correlated to learning [8] [13] [18]; hence, each rule of \( \{R_1, R_3, \ldots, R_6, R_{13}, R_{15}, R_{16}, R_{18}\} \) selects aesthetics that induce Pleasant-high emotions. The rules in this set aim to activate students.

3) Unpleasant-high emotions (e.g., frustration or confusion) may be natural and unavoidable when learning a difficult material [13] [37], such is the case of conditions required for rules \( \{R_{13} \ldots R_{24}\} \). Aiming to reduce the arousal, these rules apply aesthetics that evoke Pleasant-low emotions (e.g., calm).

4) By testing experience in educative video games, it has been found that boredom is the most persistent [13] — i.e. the detection of the same emotional state for two successive observations. Baker et al. suggested that boredom must be detected and quickly managed. On the other hand, emotional events recruit more cognitive resources — e.g., attention, distinctive processing and organization— [38] [39]. Boredom conditions are in rules \( \{R_{13} \ldots R_{18}\} \); hence, these rules suggest arousing aesthetics aiming to elevate the student arousal.

5) For the same reasons stated in the preceding point, the proposed rules avoid to induce Unpleasant-low emotions; furthermore, these aesthetics are never used and Table 2 does not have a column labeled as ‘(- LOW)’.

6) Similarly, Unpleasant-high emotions can also be an

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**TABLE 2**

Fuzzy Rules for the next stage aesthetics by considering the player emotional state and the previous aesthetics used. All the states are represented by the pair: (Valence, Arousal Level). The subscript in each cell indicates the rule number. PLEASANT emotions are represented as +, and UNPLEASANT as –.

| Player state | Previous aesthetics | (+, MH) | (+, VH) | (+, L) |
|--------------|---------------------|--------|--------|-------|
| (+, M)       | \( R_{12} \) (+, M)  |        |        |       |
| (+, H)       | \( R_{13} \) (+, H)  |        |        |       |
| (+, ML)      | \( R_{14} \) (+, ML)|        |        |       |
| (+, VH)      | \( R_{15} \) (+, VH)|        |        |       |
| (+, VH)      | \( R_{16} \) (+, VH)|        |        |       |
| (-, M)       | \( R_{17} \) (-, M)  |        |        |       |
| (-, VH)      | \( R_{18} \) (-, VH)|        |        |       |
| (-, ML)      | \( R_{19} \) (-, ML)|        |        |       |
| (-, VH)      | \( R_{20} \) (-, VH)|        |        |       |
| (-, L)       | \( R_{21} \) (-, L)  |        |        |       |
| (-, LOW)     | \( R_{22} \) (-, LOW)|        |        |       |
effective motivator for learning. In moderate to high ranges of arousal levels (i.e., the detection of a more serious threat), the aversive system is activated more agilely and vigorously than the appetitive system. However, in extremely high ranges of arousal levels (i.e., life-threatening content), the aversive system fails to identify and remember content in the external environment [30]. In this sense, rules in \{R_2, R_{14}, R_{17}\} suggest Unpleasant-high emotions when Pleasant-high aesthetics were used in the previous stage and the player still experiences low-arousing emotions (e.g., bored). To avoid extremely high ranges of arousal levels, any of these rules suggest ‘VERY HIGH’ negative aesthetics; i.e. they only suggest ‘HIGH’ negative aesthetics.

4.3 Fuzzification and Defuzzification

The fuzzification transforms the inputs into fuzzy sets in such a way that they can be used by the fuzzy system; for this aim, a simple singleton fuzzifier was used. A number of defuzzification strategies exist, each provides a means to choose a single output based on the implied fuzzy sets. A typical Center Of Gravity (COG) strategy was used [5].

4.4 Example of the fuzzy controller

An example of the complete process to estimate the arousal value for the next stage \(A_k\) is shown in Figure 3. By considering the values of this example and the proposed fuzzy rules (Table 2), only the rules \(R_{14}\) and \(R_{15}\) are fired (other rules give a value close to zero):

- \(R_{13}: \quad \text{IF} \ V \text{ is UNPLEASANT AND } A \text{ is LOW AND } V_{k-1} \text{ is PLEASANT AND } A_{k-1} \text{ is LOW THEN } A_k \text{ is VERY HIGH}\)
- \(R_{14}: \quad \text{IF} \ V \text{ is UNPLEASANT AND } A \text{ is MEDIUM AND } V_{k-1} \text{ is PLEASANT AND } A_{k-1} \text{ is LOW THEN } A_k \text{ is HIGH}\)

Analogously, the next valence value \(V_k\) can be estimated. The content selector of the proposed schema uses the pair \((V_k, A_k)\) to select the most similar sound from those available.

5 MATERIALS AND METHODS

This study investigates the pertinence of the IC method in terms of the players enjoyment, performance, and persistence of negative emotions. The following sections describe the video game, participants and metrics used in this study.

5.1 Video game

A game to practice basic math skills was designed for this study. Two versions of this game were used for the test, they have the same mechanics (e.g., both have the same game elements and states) but different dynamics and aesthetics, as explained below.

Mechanics

The game mechanics is summarized in the state diagram shown in Fig. 5. At the beginning, a random content is generated and an initial difficulty is selected. Each stage is composed of two scenes that interact with the player:

1) **Playing scene:** this is the first scene of each stage, in which 10 arithmetic operations of two numeric quantities are shown. For each operation, the player must choose the right answer by moving the falling object (using left and right keys), the fall can also be speeded up (using the down key). To obtain points, the falling object (the sum) must be introduced into the correct container (the answer) before it reaches the bottom of the screen. The game plays the selected sound each time a new sum operation is shown.

2) **Speaking scene:** this scene is intended to obtain the user’s voice. A character invites the user to speak. Once the voice is detected, the character repeats the user’s voice (modified by an effect). The scene also suggests some text to be read (guaranteeing that the excerpt is long enough to estimate the user emotional state). The user’s voice is analyzed by the emotion recognizer to ascertain the emotional state of the player.

Difficulty and aesthetic

The two games differ in the strategy employed for generating the next scene content (difficulty and aesthetic):

- Game A: It uses a simple linear DDA algorithm to select the next difficulty level. The change factor is calculated as \(F = S + 0.5\), i.e. the Change Factor \(F\) is a linear function of the Score Ratio \(S\). The new difficulty is calculated using (1). The aesthetics (sound) is selected randomly from the database.
- Game B: It uses the IC approach proposed in this paper. Once the player’s voice excerpt is obtained, the method estimates the user emotional state. For this aim, the game uses the algorithm proposed by Schuller et al. [23]. Hence, the fuzzy control suggests the new aesthetic and the difficulty level for the next stage. Finally, the aesthetic selector chooses the closest sound to the suggested.

5.2 Participants and Procedure

A total of 20 participants in secondary school from different genders participated in this experiment. Participants played two consecutive 12-minute play sessions separated by a 15-minute resting period. Each participant played ‘Game A’ for one session and ‘Game B’ for the other —the order of playing these sessions was assigned randomly. In total, 10 participants played first the ‘Game A’ and then the ‘Game B’ (and the other 10 participants first played the ‘Game B’).
Fig. 5. Calculating the next arousal value ($A_k$). In this example, the input values are: $\hat{V} = -0.722$, $\hat{A} = -0.710$, $V_{k-1} = 6.555$, and $A_{k-1} = 2.064$; hence, two rules are fired ($R_{13}$, and $R_{14}$). By defuzzifying the computed signal, the value for $A_k$ is 7.667.

Fig. 6. State diagram of the videogame used for testing. The Playing scene always precedes the Speaking scene. When playing, the user must introduce the operation (195+14) into the right container (209).

5.3 Metrics

For each participant/play session the following metrics were obtained:

- **Average Persistence of Unpleasant Emotions ($P_{UL}$, $P_{UH}$).** This metric evaluates the average number of stages spent to change the student from an unpleasant emotion to a different emotional state; i.e. once someone experiences an unpleasant emotion, it counts the number of consecutive stages where a similar emotion was detected. Therefore, this metric can only be calculated for students who experience the studied Unpleasant emotion at least once in the play session. Specifically, the study of persistence of Unpleasant-low ($P_{UL}$) and Unpleasant-high ($P_{UH}$) states is interesting. These states are considered that prevent learning; hence, it is desirable to have a low value of this metric.

- **Response Time Difference ($\Delta t$).** This metric is used to compare the participants’ performance between emotional states. Let $T_n = \{(S_{ni}, t_{ni}) \mid i = 1 \ldots N\}$ be the data obtained from the $N$ stages played by a given participant $n$, where $S_{ni}$ is the score obtained, and $t_{ni}$ is the median response time in the $i$-th stage. The performance distance of two players with data $T_m$ and $T_n$ is calculated from the last score obtained as

$$d(T_m, T_n) = |S_{mN} - S_{nN}|;$$

(2)
hence, the Response Time Difference is estimated as
\[ \Delta t_{ni} = |t_{ni} - \hat{t}_{ni}| \]
where
\[ \hat{t}_{ni} = \frac{1}{k} \sum_{T_j \in \text{Neig}(T_n)} I(S_{ni}, T_j) \]

where \( \text{Neig}(T_n) \) is the set of \( k \) nearest neighbors of \( T_n \) according to \( \mathcal{I} \), and \( I \) is a function that estimates the response time at score \( S_{ni} \) from \( T_j \) by using linear interpolation. The estimation given by \( I \) is required because \( T_j \) usually does not have a point at score \( S_{ni} \).

- **Last Score** \((S_N)\). To compare the difficulty level between control strategies. Given the data log \( T_n = \{(S_{ni}, t_{ni}) \mid i = 1 \ldots N\} \), the last score is
  \[ S_N(T_n) = S_{NN}. \]

- **Number of Reduction Hops** \((H^-)\). An ideal adaptive difficulty level must increase the difficulty level as the player increases her/his knowledge and abilities about the problem. A reduction hop—a perceptible level increase followed by a perceptible decrease—is undesirable. In this sense, the difficulty level must be a non-decreasing function. For accepting minor changes, this metric considers a reduction hop when
  \[ \frac{D_k - D_{k-1}}{D_{k-1}} \leq -\epsilon, \]
a value of \( \epsilon = 0.02 \) was used for the tests.

### 5.4 Statistical analysis
Data are represented as mean ± S.D. and the significance was assessed by Student’s t-test for paired data. A Wilcoxon Signed-Rank Test was used to compare the speed difference in different emotional states. For all cases, differences between values were considered significant when \( p < 0.05 \).

### 6 Results and Discussion

#### 6.1 Results
A simple comparison between DDA and IC strategies can be done by integrating the emotional state of each stage for all players. The overall comparison of the proportion of stages by groups is shown in Fig. 7. The overall proportion of pleasant-high states are higher for IC (33.93%) than for DDA (26.95%). Besides, the overall proportion of Unpleasant-high states are lower for IC (26.79%) than for DDA (36.53%).

It is also interesting to study the overall progression from one emotional state to another. The emotional state transitions for consecutive stages is shown in Table 3 that is, the table shows the estimated probability of change from a given player emotional state at stage \( k \) to another emotional state at stage \( k + 1 \); e.g., when the emotion of a player is Pleasant-low at stage \( k \), the probability of changing to Pleasant-low state at the next stage is 0.429 for DDA and 0.467 for IC. There are lower proportion of self-transitions in Unpleasant-low states for IC (0.514) than for DDA (0.661), and a lower proportion of self-transitions in Unpleasant-high states for IC (0.5) than for DDA (0.664). It means that the IC can diminished the self-transitions of negative states.

Table 4 shows the general statistics for the metrics \( P_{UL} \), \( P_{Uh} \), \( H^- \), and \( S_N \) (these metrics are described in Section 5.3). There was a significant difference in the persistence of Unpleasant-high emotions \((P_{UL})\) for IC and DDA approaches; \( t(20)=2.56, p=0.019 \). Furthermore, the average number of stages to change a student from Unpleasant-low emotions to another kind of emotion is almost twice for DDA (2.23 stages) than for IC (1.14 stages). Even though lower persistence of \( P_{UH} \) was observed in average (1.52 for IC and 2.04 for DDA); there was not a significant difference in the persistence of Unpleasant-high emotions \((P_{UH})\) for IC and DDA approaches; \( t(15)=1.62, p=0.129 \). There was also more Reduction Hops \((H^-)\) for DDA than for IC; \( t(20)=3.27, p=0.004 \). There was not a statistical difference in the maximum Score for IC and DDA approaches; \( t(20)=-0.936, p=0.361 \).

Finally, as shown in Table 5 the response time is slower for players in Unpleasant-low emotions than other emotions; \( W=5091, p=0.012 \).

#### 6.2 Discussion
Changes in core affect result from a combination of events. For each individual, there are genetically based individual
differences and internal temporary causes —e.g., activity of immune cells, diurnal rhythms, and hormone changes. External causes that could change the core affect work on this floating baseline [18]. It implies that sometimes an external cause, such as the change of aesthetics, cannot induce a desirable emotional state. Despite this, the experimental results show that the proposed Inductive Control is able to reduce the persistence of Unpleasant-low stages \((P_{UL} = 1.14)\) for IC and 2.23 for DDA). This effect is also shown in Table 3 in which the self-transition for Unpleasant-low state is lower for IC (0.514) than for DDA (0.661). Boredom can also be caused by low difficulty [8], but results show that it was not a significant difference in the difficulty level reached at the end of each play session \((S_N)\) between DDA and IC strategies.

The self-transition between Unpleasant-high is lower for the IC than for DDA (Table 3), and the mean persistence of Unpleasant-high emotions is slightly lower for IC than for DDA (Table 4); but, there was not a significant difference.

### TABLE 3
Comparing emotional state transitions for DDA and IC. As shown in bold, the self-transitions of Unpleasant-low and Unpleasant-high states are lower for IC than for DDA.

| (E. State)_k | DDA | IC |
|--------------|-----|----|
| (Emotional State)_{k+1} | | |
| Pleasant Low | 0.429 | 0.467 |
| High | 0.026 | 0.000 |
| Unpleasant Low | 0.071 | 0.022 |
| High | 0.000 | 0.026 |

### TABLE 4
Comparison of the adaptive against inductive control strategies \((N = 20)\). Better results are shown in bold.

| Algorithm | DDA | IC |
|-----------|-----|----|
| \(P_{UL}\) \((\text{stages})\)\textsuperscript{1} | 2.23 ± 2.10 | 1.14 ± 1.11 |
| \(P_{UH}\) \((\text{stages})\) | 2.04 ± 1.89 | 1.52 ± 1.49 |
| \(H^\dagger\) \((\text{stages})\) \textsuperscript{1} | 0.60 ± 0.82 | 0.00 ± 0.00 |
| \(S_N\) \((\text{points})\) | 253 ± 184 | 276 ± 242 |

\textsuperscript{1}Significant difference

### TABLE 5
Speed difference \((\Delta t)\). Students in negative-low arousal states respond in average 0.119s slower than the predicted value, while students in other emotional stages respond 0.689s faster than the predicted value.

| Emotional Stage | DDA | IC |
|-----------------|-----|----|
| Unpleasant-low | 0.119 ± 1.565 | 0.016 ± 1.565 |
| Pleasant or high | 0.689 ± 1.754 | 0.689 ± 1.754 |

\textsuperscript{1}Significant difference

This can be caused by the strategy of relaxing students when they are frustrated (fuzzy rules \(R_{19-24}\)) is directly competing with the natural increase of video game difficulty. Unpleasant-high emotional states not always require remediation [41], since such states (e.g., frustration or confusion) are related to learning and are linked to learning gains [13].

It was also observed a significant difference in \(H\) between IC and linear DDA strategies. This can be explained because unnecessary radical changes are avoided in the difficulty adjustment control based on fuzzy logic. Although radical changes can help to reach faster the flow zone, they may also cause difficulties to keep the player in flow (Fig. 8). The Gaussian membership functions (Fig. 5) help to make soft changes in difficulty. There is a drawback to Gaussian membership functions: they extend from negative infinity to positive infinity. That fact entails the firing of all rules all the time, even for infinitesimal values of the membership function of the variables involved in the systems inference rules.

Since a Gaussian function tails quickly become insignificant, this problem is solved by rounding to a fixed number of decimal places, thus chopping their tails.

Finally, it was a significant difference in \(\Delta t\) between Unpleasant-low and other emotional states (Table 5), it means that the time response of players in Unpleasant-low states is slower than the time response of players in other states. It verifies that participants are less concentrated in those states as suggested in many studies [13, 42].

Based on the previous facts, we argue that the aesthetic change can induce desirable changes in students, able to avoid non-learning emotional states.

### 7 Conclusions and Further Work

Unlike other approaches that only adjusts the game level, the proposed technique also induces emotions in the player for supporting the learning process.

The overall results show that in comparison to DDA, IC increases the proportion of stages were the students experienced Pleasant-high emotions and reduces their Unpleasant-low stages. This effect was mainly caused by the reduction of transitions of unpleasant emotional states. Specially, the participants changed faster from Unpleasant-low to Pleasant or High emotions. The Unpleasant-low is considered an unlearning state, hence it must be avoided because it can make it difficult for students to complete some tasks. This study showed that these states cause a decrease in response time.

The difficulty control strategy based on fuzzy logic and Gaussian membership helps students to smoothly reach their “flow zone” and once reached, it helps to keep students in flow.

In conclusion, a systemic approach that controls the difficulty of the learning material, and the mechanics, dynamic and aesthetic of the video game could be a valuable tool. To the authors’ knowledge, this is the first effort to adjust both the difficulty and aesthetics of the game using a fuzzy control based on the learner actual development and emotional state.

Currently, we are studying the IC approach in other learning settings (e.g., to accomplish a learning objective), with more elaborated mechanics. We are also implementing...
machine learning strategies to automatically generate rules and membership functions.

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