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Guided Emotional State Regulation:

Understanding and Shaping Players' Affective Experiences in Digital Games

Pedro A. Nogueira[1,3,4], Rui Rodrigues[2,3], Eugénio Oliveira[1,3], Lennart E. Nacke[4]
[1]Artificial Intelligence and Computer Science Laboratory, [2]INESC-TEC, [3]University of Porto, Portugal
[4]GAMER Lab, University of Ontario Institute of Technology, Canada
{pedro.alves.nogueira, rui.rodrigues, eco}@fe.up.pt, lennart.nacke@acm.org

Abstract

Designing adaptive games for individual emotional experiences is a tricky task, especially when detecting a player's emotional state in real time requires physiological sensing hardware and signal processing software. There is currently a lack of software that can identify and learn how emotional states in games are triggered. To address this problem, we developed a system capable of understanding the fundamental relations between emotional responses and their eliciting events. We propose time-evolving Affective Reaction Models (ARM), which learn new affective reactions and manage conflicting ones. These models are then meant to provide information on how a set of predetermined game parameters (e.g., enemy and item spawning, music and lighting effects) should be adapted, to modulate the player's emotional state. In this paper, we propose and describe a framework for modulating player emotions and the main components involved in regulating players' affective experience. We expect our technique will allow game designers to focus on defining high-level rules for generating gameplay experiences instead of having to create and test different content for each player type.

1 Introduction

In game research, we currently do not understand how to best use human emotions for more immersive and engaging gameplay experiences. To this end, we believe that the full potential of emotions in shaping gameplay has yet to be explored. In this paper, we interpret emotional states as individual psychophysiological experiences that are shaped by biochemical interactions and environmental stimuli. As they occur at a—mostly—subconscious level, emotions influence humans in a meaningful and critical way, often overriding rational thought. Thus, we believe that using the player's emotions as catalysts for a biocybernetic emotion regulation loop (Fairclough 2009) embedded in a game engine can improve the overall user experience. In this paper, we describe a framework to regulate players' affective experiences. Given the rather formal nature of this description, we also present a practical example of how we are adapting an indie videogame to use this framework and some considerations on the framework's implementation.

Motivation

In the past two decades, video games have pioneered breakthroughs in fields such as computer graphics, animation, artificial intelligence, physics simulation and interaction techniques. These achievements were propelled by a popular demand for more realistic experiences and produced more believable virtual environments, characters, audio-visual effects and interactions. Despite these consecutive improvements, we are now going through a slower evolution consisting mainly of iterative enhancements.

As video games move towards photorealistic graphics, the game research community has started focusing their efforts on promising and yet underexplored areas of the gameplay experience. We have seen a deep analysis of what motivates gamers to play (Ryan et al. 2006) and of what constitutes a good gaming experience (Ermi et al. 2005). One of the conclusions of this prior research was that video games are played either to: *a)* live out a fantasy, or *b)* to relax/escape from the problems of everyday life—at most times a combination of both. In either of these cases, a common trait is often considered: *video games must provide an engrossing experience, through which players can immerse themselves in the virtual world*.

The concept of immersion dates back to early virtual reality systems and it referred to how enveloped the user's senses were in the virtual world (Brown et al. 2004; and Jennett et al. 2008). However, immersion is currently a disputed concept as few academic definitions exist and it is often used as a buzzword in game journalism and marketing campaigns. Despite this, in most definitions of immersion and gameplay experience, the presence of strong emotional bonds with the game world is a constant factor. These bonds occur either through strong visceral reactions to game events (e.g., scares, awe at the scenery, intense firefights) or through more lasting emotions (e.g., empathic bonds with game characters or narratives). This leads us to believe that affective attachment is the hallmark of a memorable gameplay experience.

Emotional Regulation

Emotion regulation is considered an important driver of affective computing (Picard 1995). However, it is a concept closely tied to behavioural psychology and—for our purposes—requires a definition in a computational context. According to Gross et al. (2009), emotion regulation usually refers to "*an individual's ability to evaluate, understand and modulate their emotional responses to events according to some strategy.*" These strategies may target managing uncomfortable emotions, engaging in socially acceptable conduct or avoiding pathological behaviour. While emotional regulation may be self-induced, other uses of the term may refer to employing a certain type of therapy where emotions are used to influence the patient.

In our work, we redefine the term within the context of digital video games and interactive multimedia scenarios as: "*A process through which users' emotional responses are induced by a set of carefully chosen stimuli, aimed at eliciting a certain emotional state or pattern over time*". The process is further delineated by three separate phases that should occur continuously and in parallel:

I. Modelling and monitoring the user's emotional state in real-time
II. Providing emotionally-charged stimuli as a means through which the emotional state is modulated to the desired states or patterns
III. Observing the user's emotional responses to each stimulus, while storing them for future reference.

2 Related Work

Emotion Recognition

Various successful attempts have been made in the field of emotion recognition by using physiological computing. For instance, Chanel et al. (2006) were able to classify arousal using naïve Bayes classifiers based on electroencephalographic (EEG), skin conductance (SC), blood volume pressure (BVP), heart rate (HR), skin temperature and respiration (RSP) rates. Complementary, the work conducted by Leon et al. (2007) classifies valence in three intensity levels via similar measures (SC, its time gradient and derivative, HR and BVP) coupled with auto-associative neural networks (NN). Haag et al. (2004) have also proposed a similar NN-based approach, achieving 89% accuracy for arousal and 63% for valence (with a 10% error margin), through EMG, SC, skin temperature, BVP, ECG and RSP metrics. In fact, the study presented by Drachen et al. (2010) confirms that relatively simple features extracted from SC and HR measures are indeed highly correlated with reported affect ratings in gameplay scenarios. A more detailed study has also found proof that features extracted from HR, SC and BVP can be used to predict higher-level concepts, such as "fun" in a game-dependent manner (Yannakakis, and Hallam 2008).

Finally, both the works presented by (Vinhas et al. 2009; and Mandryk 2005) propose systems capable of continuously measuring both arousal and valence in real-time using SC, HR and, in the latter, facial EMG readings.

Biofeedback & Experience Modelling

One of the earliest works in biofeedback techniques was presented in Konami's dating simulator "*Oshiete Your Heart*", where the player's BVP and SC levels influenced the result of the date. A later title, Tetris 64, released for the Nintendo64 platform featured an ear sensor that monitored the player's heart rate, using it to modulate the game's speed. Atari also tested an EEG sensor called Mindlink in the 1980s, but the prototype never left the lab. Due to their simplicity and cost at the time, these systems were seen as obtrusive and unreliable gimmicks that were easily manipulated and failed to add significant depth to the game. However, the recent popularity of affective computing has motivated the resurfacing of new and improved affective and physiological games (Nacke et al. 2011; Pedersen et al. 2009; and Leite et al. 2010).

Regarding the use of biofeedback mechanisms for emotional state regulation in multimedia applications, work has been done in the fields of direct affect responses (Leite et al. 2010; Kleinsmith et al. 2003; and Bernhaupt et al. 2007), biofeedback control mechanisms (Nacke et al. 2011) and player experience influencing (Pedersen et al. 2009; and Figueiredo et al. 2010). Regarding direct affect response, Kleinsmith et al. (2003) attempted to interpret emotional states through body posture and react accordingly to a given context. Similarly, Leite et al. (2010) presented an empathic robot capable of reacting to contextual information. In the realm of videogames, Bernhaupt et al. (2007) has contributed with a simple emotionally driven game that uses players' facial expressions to directly control the growth rate of virtual flowers. Using more complex mechanisms, Nacke et al. (2011) explored the effects of both direct and indirect physiological control in a 2D platform shooting game, concluding that each type has its own adequate uses for shaping gameplay experience.

While not physiologically-driven, the works presented by Figueiredo et al. (2010) and Pedersen et al. (2009) support that complex game aspects such as storyline and gameplay parameters can be dynamically adapted to individual players in order to achieve a predetermined reaction. Despite using correlations to questionnaire-based affect ratings instead of a physiological approach, these works present strong proofs of concept towards systems capable of influencing player experience. We propose that instead of indirectly adapting game-specific parameters via subjective data, a more direct approach be taken through implicit biofeedback mechanisms driven by the user's own physiologically measured emotional state variations over time.

In sum, the presented approaches serve as proofs-of-concept for the implementation of emotion reaction mechanisms in videogames and other affective computing applications. They provide supporting evidence that this specific kind of interaction does in fact influence the player experience and can thus be used to benefit it. However, the current state of the art focuses either on: *a)* using static rules to reactively trigger fixed events once an emotional state has been observed (Nacke et al. 2011; Leite et al. 2010; Cavazza et al. 2009; and Bernhaupt et al. 2007), and/or *b)* in mimicking emotional responses on behalf of an AI agent (Cavazza et al. 2009; Kleinsmith et al. 2003; and Bernhaupt et al. 2007). Thus, these approaches are limited because the application provides players with affective information, but does not take into account the reactions this same information elicits (i.e., it either ignores, or assumes, a fixed reaction instead of taking into account the changing nature of the provided emotional influence). As a result, the system has no feedback on how this information is perceived by the player and what mental state it elicits. As such, it is unable to learn from these interactions and adapt to each player. In our view, these approaches are not really capable of closing the biofeedback loop and thus, are not fully bi-directional. We address this problem by proposing a bi-directional interaction scheme that strives to adapt its actions based on the observed user reactions. By doing so, we expect to be able to implement both the ACE model (Gilleade et al. 2005) and address all of Hudlicka's affective engine requisites (Hudlicka 2009):

1. Recognise a wide emotion gamut in real-time
2. Provide mechanisms to respond to affective states
3. Dynamic construction of affective user models.

3 Proposed Framework

Framework Architecture

To investigate our research question – whether emotions can be used to regulate players' affective experience – we propose the Emotion Engine (E^2) biofeedback loop system.

In order to study the effects of emotions on user experience and using them to shape players' reactions, several issues must first be addressed:

- Develop a generic method for measuring emotional states. It should provide a continuous measure of emotion in real-time, while also requiring as minimal pre-usage calibration as possible
- Propose a methodology to: *a)* automatically associate emotional reactions to their eliciting events, and *b)* compile the user reactions into a time-evolving affective reaction profile (ARP)
- Define a method to leverage the user-collated data in order to reinforce a set of desired emotional states and patterns.

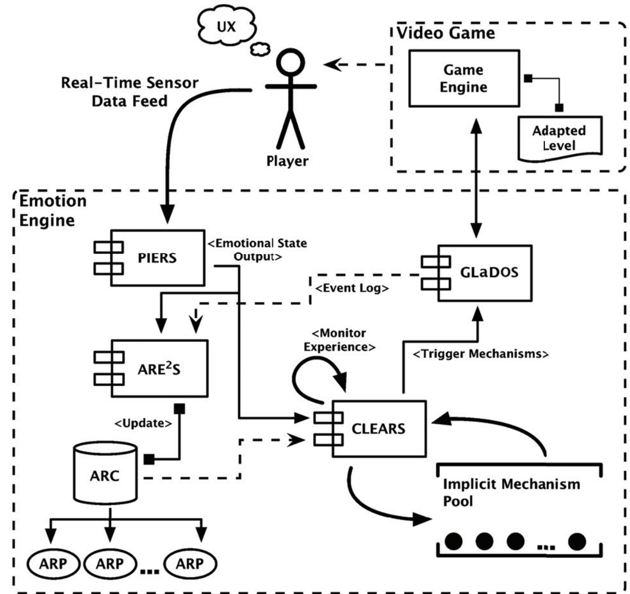

Figure 1. The E^2 architecture.

Each of these issues is addressed by a separate component of our architecture. These can be seen in Figure 1, which presents a summary description of the architecture's general working principles. In essence, as the player experiences the game, his emotional state is reflected in his real-time physiological readings. This emotional state (ES) is then interpreted through the sensor feed by PIERS, which communicates any changes to the ARE^2S and CLEARS components. These components then each perform two other crucial tasks: *1)* identify and create the player's affective response profile (ARP) and *2)* regulate the player's affective experience based on what is known of his emotional preferences. ARE^2S creates the player's ARP by associating the changes in his emotional state output to the occurring events, which he obtains from GLaDOS – a generic game-interfacing module. On the other hand, CLEARS constantly monitors the player's ES and, if it deviates from the desired ES range, selects the most suitable implicit mechanism (game event/parameter) according to the player's ARP. The following sub-sections describe each of the aforementioned components in greater detail.

PIERS

The first step in the emotional regulation process is determining an, although simplified, relevant to our needs image of the user's current emotional state. To this end, we have developed the Physiologically-Inductive Emotion Recognition Sub-system (PIERS), which is responsible for classifying the user's emotional state in Russell's arousal/valence (AV) space (Russell 1980).

The developed method categorizes participants' AV ratings through a two-layer classification process (see Figure 2). The first classification layer applies several regression models to each of the four physiological inputs (SC, HR and facial EMG), which allow us to simultaneously normalize these inputs and correlate them to the AV dimensions. The second classification layer then combines the arousal and valence ratings obtained from the previous step into one final rating by averaging the models' residual sum of squares (RSS) error.

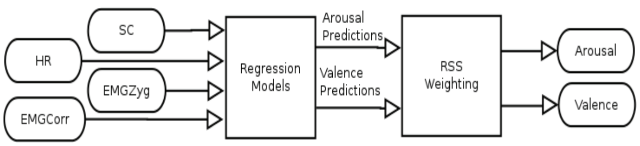

Figure 2. High-level view of the PIERS architecture.

Through this methodology, we have achieved convincing accuracy ratings (85% for arousal and 78% for valence), while at the same time successfully predicting these states in a continuous manner and without requiring complex calibration or parameter tuning procedures prior to its usage. However, due to space limitations, discussing the system's development and validation process is out of the scope of this paper. We thus refer the reader to (Nogueira et al. 2013a) for an in-depth description.

ARE^{2}S & ARC

However precise, successfully initiating the emotion regulation process requires more than simply knowing the player's emotional state. The system must determine which regulation mechanisms should be triggered, given the player's past reactions. Extracting this information from the player/video game interaction falls upon the Affective Reaction Extraction and Extension Sub-system (ARE^{2}S).

ARE^{2}S achieves this by obtaining the game log stream (see next subsection), and linking the logged events to PIERS's emotional state output. This causality relation is determined by identifying the highest change in local maxima/minima (LMM) – herein referred to as an emotional state transition –, for each dimension of the AV space, subsequent to each event. The affective reaction mapping function (Φ) is therefore defined as:

$$\Phi : \Lambda X \Omega \rightarrow \vec{w} \quad \sum_{i=0}^{len(\Lambda)} \overrightarrow{w_i} = 1 \;\wedge\; \overrightarrow{w_q} \in [0,1]$$

Where Λ is the set of possible emotional states – discretized from PIERS' continuous output – and Ω the set of possible events. Thus, the Φ function receives an emotional state λ, such that λ ∈ Λ and an event ϖ, such that ϖ ∈ Ω, and outputs a weight vector $\vec{w}$ that contains the probabilities of observing a transition to each of the possible states Λ ($|\Lambda| = |\vec{w}|$), if the considered event ϖ is performed at the current emotional state λ.

In order to compute the transition weights $\vec{w}_i$, we must first amass a set of observed transitions *T*, where we store each transition according to its chronological order. *T* is thus defined as a 3-tuple of the form: $t_a = (\lambda_i, \lambda_f, \varpi)$, where λ_i is the LMM emotional state preceding an event ϖ and λ_f is the LMM emotional state posterior to the same event ϖ. Updating the transition probability vector $\vec{w}$ for transition tuple ta is computed by applying the following exponential averaging function with a learning rate α:

$$\vec{w}_i = \begin{cases} \vec{w}_i\alpha + (1-\alpha), \; if \; i = f \\ \vec{w}_i\alpha, \; otherwise \end{cases}$$

Each transition vector $\vec{w}$ is created with an equally distributed transition probability $p_i = |\Lambda|^{-1}$ for all possible transitions. However, the developer can manually define the values, if he has *a priori* information on how users might react or wishes to set initial biases towards certain events.

By re-computing the probability values for each new observed emotional transition t_a, we expect our system will be able to learn how users react to game events over time and compensate for traditional habituation effects, leading to more accurate predictions of future reactions. Finally, the Affective Reaction Compendium (ARC) represents a database containing the full set of amassed affective reaction profiles (ARP) for each user.

CLEARS, GLaDOS & IMP

Complementary to ARE^{2}S, the Closed-Loop Emotional Adjustment and Regulation Sub-system (CLEARS), is responsible for monitoring and eliciting the predetermined emotional states/patterns. CLEARS does so by monitoring the user's emotional state and triggering the events that minimise the distance d to the desired ES in the AV space, such that d is given by the Euclidean distance between two emotional states (λ, λ'):

$$d(\lambda, \lambda') = \sqrt{(\lambda_a - \lambda'_a)^2 + (\lambda_v - \lambda'_v)^2}$$

However, since we cannot be fully certain of which transition will occur (if any of the previously observed ones), we cannot base our decisions on this distance metric alone. This implies the entropy associated with the transition function must be taken into account in the event selection process. We do so using the concept of risk (Ψ), which we define as follows:

$$\Psi(\lambda,\varpi,\lambda') = 1 - \Phi(\lambda,\varpi)_{\lambda\prime}$$

In sum, the risk ψ associated with performing an event ϖ at a certain emotional state λ, while expecting a transition to a new emotional state λ' is given by the complement of the transition probability to that same state λ', obtained through Φ. The event selection process thus becomes a probabilistic optimisation problem in which we must minimise both the distance to the desired state λ^f and the risk involved in its choice – under the penalty that the occurring transition moves us even further from λ^f. We approach this issue in the following way: consider the set of all possible actions in Ω in the current emotional state λ and assume that the risk for each of the possibly occurring transitions $\psi_{\lambda,\varpi,\lambda'}$ represents the probability that an unknown and maximally entropic deviation ξ in the expected final state λ' will be observed. Furthermore, assume ξ to be a random number in the $[0, \rho]$ interval, where ρ is equal to two times the standard deviation in $\Phi(\lambda,\varpi)$. In other words, assume that the greater the risk, the more likely it is a random transition within 95% of the distribution of previously observed transitions will occur instead. The optimal event ϖ' is the one that satisfies the following condition over all possible events in Ω:

$$\min(\, d(\lambda',\lambda^f) + \Psi(\lambda,\varpi,\lambda')R(0,\xi)\,) :$$
$$\xi = 2\Gamma(d(\lambda,\lambda')[\Phi(\lambda,\varpi)])$$

Where, *R(a,b)* denotes a function that returns a random number sampled from a uniform distribution in the $[a, b] \in \mathbb{R}$ interval, and $\Gamma(\vec{v})$ a function that computes the standard deviation of a tuple vector $\vec{v}$.

GLaDOS, the Game Layer alteration Daemon Operating Script is a generic interfacing module used to trigger the events. Our current implementation relies a set of *callback* functions bound to a script set programmed into the game's logic. Finally, the Implicit Mechanism Pool (IMP) consists of all the available events that can be triggered to influence the user. This static pool of events is a configuration file with information on how each event can be triggered through GLAD (e.g., keystroke binds or function *callbacks*), in order to make the framework modular.

4 Applicational Case Study

Given the rather abstract and dense description of the framework so far, we consider a more practical narrative may be of some use towards readers interested in a practical approach. The following example depicts our adaptation of the indie game Vanish (Figure 3) to the E^2 architecture. Vanish is a survival horror videogame where the player must navigate a network of procedurally generated maze-like tunnels to locate a set of key items, before being allowed to escape. While navigating these tunnels, the player must evade a creature that continuously stalks him. Other events (e.g. lights failing, distant cries or steam pipes bursting without notice) also occur quasi-randomly, in order to keep the player about his wits.

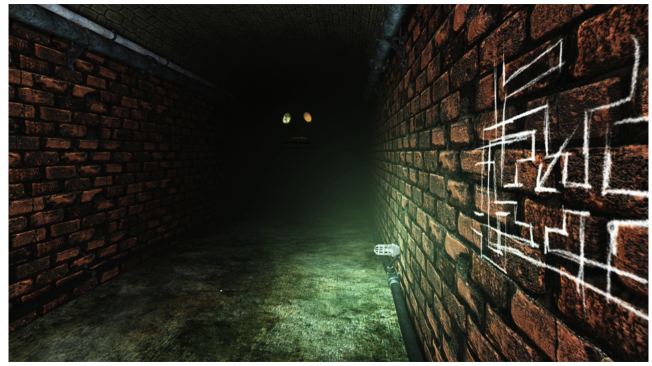

Figure 3. Screenshot of a Vanish gameplay session, showing the creature lurking in the distance.

Adapting Vanish to the E^2 architecture has occurred in three steps. Firstly, we provided the architecture with access to the game through the GLaDOS interface. Through it, the system notifies the game when to trigger each event. The game also has to push notifications for each event through GLaDOS so that the players' reactions to each of them can be learned and stored in his ARP. Having linked the game and our system, we defined a series of parameters regarding this particular game:

1. How often the system is allowed to trigger events
2. Which events are logged (and later triggered)
3. What range of emotional states the system should aim to elicit.

While in this case the events to be learned constitute the full set that can be triggered, there may be times when a developer does not wish for a certain subset of these events to be available (e.g. when enemies are specific to a certain level, or during key game sections). As such, at each given time the developer is able to, through GLaDOS, inform the E^2 which events are allowed. Much in the same manner, a level (or level section) may be tuned for a specific type of emotion and, as such the developer only needs to define which emotional states are to be targeted at each instant.

The third step regards the experimental setup required to obtain the player's ES output (see Figure 4) and is perhaps the largest difficulty in the practical application of our system. Our current solution, while not overly intrusive or expensive, still requires specific hardware and a – despite singular – calibration of each physiological channel. This implies that each new player has to undergo a calibration process - refer to (Nogueira et al. 2013b) for an in-depth discussion. Since our system is not reliant on our particular implementation of PIERS, it is possible to either simplify the ES classification process or seek alternate emotional state identification techniques (e.g. facial recognition, keypad pressure, interaction patterns, etc.). However, these mostly come at the cost of higher calibration, system train

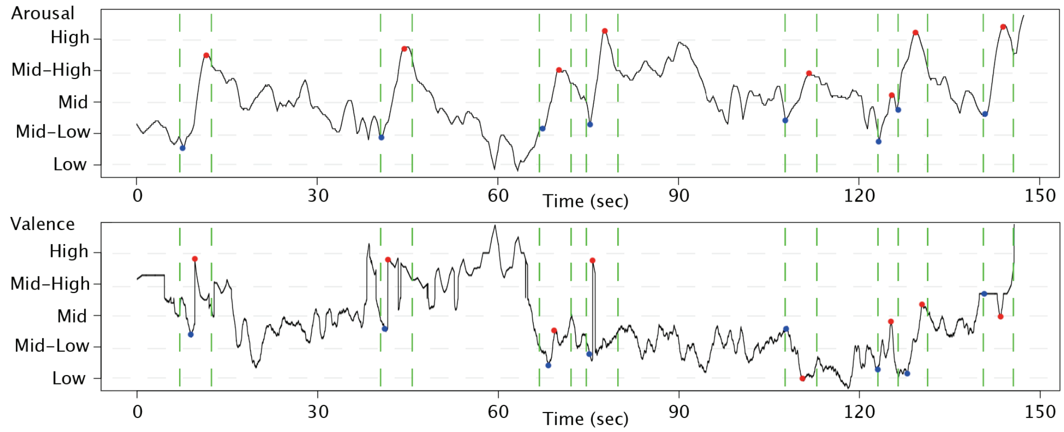

Figure 4. Example of a player's ES classification output over 150 seconds. Notice that PIERS' continuous output was re-interpreted and discretized into 5 levels for both arousal and valence. The figure shows how ARE^{2}S would identify each logged event: blue circles denote the identified prior LMM emotional state at the start of the logged event; red circles denote the identified response LMM. The green dotted lines represent the time window (5 seconds in this example), under which the ES output is analysed for each event.

ing or loss in prediction accuracy/resolution. It falls upon the developer to weigh his personal needs against these issues. An alternative approach is to take a lesson from natural interaction techniques (e.g. Kinect and WiiMote) and *gamify* the calibration process, effectively masking it within the game's initial tutorial sections.

5 Discussion

Parallel to our proposed work, being able to adapt the user-specific content opens many possible improvements: from more human-like or emotionally aware NPCs, to evolving intelligent narrative systems or targeted emotional advertisement. The following paragraphs discuss some of the benefits we expect to achieve with our research.

A common issue brought up by most consumers is that "content lifetime" (*replayability* in video game parlance) is steadily decreasing. This is mainly due to the increasing game content complexity and its inherent time and production costs. Allowing the content to become *morphanthropic*[1] could potentially alleviate these issues and provide buyers with more content for their money in the meantime.

Also, since multimedia content is designed to convey a certain affective experience, designers must strive to convey their visions. Due to the content's asynchronous production and consumption, designers must achieve this indirectly by combining the stimuli that best convey the desired meaning to the majority of the target audience. It is inevitable that by being forced to choose a fixed stimulus set, some of the meaning will be lost to a part of the audience. By delegating the stimuli choice to a mechanism that is able to monitor the player's responses it becomes possible for the designer to dedicate their attention to other aspects of the game/application and rely on high-level rules for eliciting the correct affective experience.

It has become increasingly clear that emotions drive peoples' experiences in video games. Still, understanding how they can be used to provide a targeted gameplay experience remains an unsolved issue. This work attempts to tackle this issue through a system capable of understanding the causality relations between physiologically measured emotional response variations and their eliciting events.

In this paper, we described the five principal components of our proposed framework, in addition to a practical applicational case study. With this work, we hope to contribute with an initial, real-time method for automatic emotional regulation method that can be generically applied to videogames and other multimedia applications.

Our current research focus now lies in examining if there are any significant correlations between various features of the users' emotional states and reported gaming experience ratings. We expect this study will allow us to determine the optimal emotional states to elicit in order to enrich the gaming experience and predict user experience ratings from their psychophysiological state.

Acknowledgments

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[1] A portmanteau between the words morph meaning, "*to transform*" and anthropic, meaning "*of or relating to human beings*". In this paper we coin the term morphanthropic an adjective describing "*(an element with) the ability to transforming itself in regards or by relation to human beings*".

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