Towards Tailoring Player Experience in Physical Wii Games: A Case Study on Relaxation

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ABSTRACT

In this study we construct an artificial neural network model of players' relaxation preferences while playing a physical Wii game. Developed technology will assist game designers to automate a part of the game design and balancing features, and create physical Wii games with adaptive experiences for the player. The model is trained on data derived from the player-Wii interaction which include physiological response, Wii Remote gesture and game data. In this study the developed relaxation model proved to achieve a highest classification accuracy of 78.42%. Furthermore, the restriction of input data to Wii Remote specific features and the possibility of using this model for tailoring the player experience are discussed.

Categories and Subject Descriptors

I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems – *Games*.

H.1.2 [**Models and Principles**]: User/Machine Systems – *Human factors, Human information processing*.

K.8 [**Personal Computing**]: General – *Game*.

General Terms

Algorithms, Measurement, Performance, Design, Human Factors, Experimentation.

Keywords

Affective Computing, Physical Interactive Games, Physiology, Tailoring Player Experience, Emotion, Machine Learning

1. INTRODUCTION

The game industry practice for making games is a team of game designers, artists and level designers, amongst others, that realise their ideas into a game and often expect that the player experience is as imagined. However, there exist different player types [1] with dissimilar playing styles that might experience the game differently. To overcome this, applying affective computing [2] techniques to video games make it possible to develop computational models that recognise the players' emotional state and can be used to tailor the player experience as intended by the game designers.

The goal of this study is to develop a relaxation model that, based on the model's outcome, can adjust in-game control parameters to generate a selected relaxation state. Such technology can for instance assist the development of adaptive physical games suited for physical therapy and rehabilitation.

2. RELATED WORK

In recent years the interest in emotions recognition research has grown rapidly and has advanced into numerous studies of emotion measurement [3]. Emotions are complex processes and arouse numerous changes and responses among the behavioural, physiological and subjective systems of the body; therefore it is difficult to measure them precisely. Researchers (Lang [4], Schachter [5], and Scherer [6]) argue that facial and vocal expression, and physiological changes – like for example: increasing heart rate (HR) and sweaty hands (increasing skin conductance[1] (SC)) co-occur with emotions, and measuring such user response can help in indentifying emotions accurately. The patterns in emotion response and expression can be "person-dependent" and vary in many ways. This can be due to many factors, such as temperament, personality, gender, context, and social and cultural expectations [2]. These issues can be resolved by building an emotion recognition system that is based on machine learning and pattern recognition, which can determine which features are the best emotion predictors for each individual.

Yannakakis, et al. [7] developed an artificial neural network (ANN) model that can capture players' level of reported fun while playing physical activity games built on physiology signal input and fun preferences. Another example is the study of McQuiggan, et al. [8] that investigates which of the following three machine learning techniques: induced decision trees, naïve Bayes or Bayesian Network, is the most accurate in mapping the player's physiology data to emotions. There are many other similar affective modelling studies in the literature but discussing them is out of the scope of this paper.

This experiment follows the experimental methodology proposed by Yannakakis, et al. in [7] and constructs a model for predicting Wii players' reported relaxation preference. The novelty of this study lies in the application of an existing methodology to a new domain, specifically to a physical Wii game.

3. METHOD

For building the proposed affective computational model, the following four steps are taken:

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[1] The skin conductance response is the electrical resistance of the skin i. e. sweat in hands.

1. To tailor the player experience some game variables – factors that influence the player experience – need to be mapped to the players' relaxation state. The psychological study by Malone [9] identifies three factors that influence the players' engagement and experience in games: challenge (how hard/challenging the goals in the game are), curiosity (how predictable the game states are) and fantasy (mental images of physical objects and social situations). Challenge and curiosity are chosen to be the variables (i.e. controllable game factors) used to generate different variations and experiences from one game. The challenge and curiosity factors are quantified and three different states (*low*, *medium* and *high*) are designed for each factor. All combinations of these controllable parameters are used to generate nine variants of the game i.e one game can be generated from the combination "*low* curiosity" and "*high* challenge".

2. A user study is designed that uses a Wii test-bed game, questionnaire and sensors to gather the following data from the player: a) Blood Volume Pulse[2] (BVP) and SC signals, b) motion acceleration data from the Wii Remote, c) interaction data from the game, and d) user reported pair-wise relaxation preference data from different variants of the game.

3. A machine learning algorithm is used to learn the association between the following factors: physiology signals data (SC, BVP, and HR), players' selected relaxation preference and the game interaction and gestures data.

4. The last step is to use the trained relaxation model to tailor the players' experience in real-time. For this purpose, the specific controllable game features – challenge and curiosity – would be used to change the players' relaxation. The intention of this model is to predict how the relaxation state changes relating to controllable game factors and physiology and Wii features, and thereby making it possible to guide the players' experience towards a specific relaxation state.

3.1 The Wiizards Test Game

In order to construct the computational model a test-bed Wii game **Wiizards** was developed. **Wiizards** is a single player magic fighting game in which the player embodies a role of a wizard and fights against an enemy wizard. The Wii Remote in the game represents a magic wand that the player uses to "perform magic" with by doing certain gestures. The players can chose from 3 spells: Lightning, Fireball, or Shield spell. When a player is under a lightning attack, she can break out by shaking the Wii Remote heavily.

The player is fighting an enemy wizard that is computer-controlled and can be adjusted according to the controllable features in the game i.e. the curiosity (*cu*) and challenge (*ch*). The purpose of the game is to win all fights against the opponent, which defines the game goal of any fighting games. The controllable feature challenge is defined to be the magic performing speed of the computer-controlled opponent and curiosity is defined as the choice and the order of magic spells that the opponent selects.

[2] Blood volume pulse is the blood pressure in the extremities; heart rate can be calculated from this signal.

Figure 1. A screenshot of the test-bed game during gameplay where the player is under lightning attack from the opponent

4. USER STUDY

In order to collect the data needed for training the relaxation model a user study was conducted at a primary school using pupils at the age group 13-16. To keep the experimental effect as low as possible the participants played the game alone in a customised room. The users' reported relaxation preference was gathered via a questionnaire that asked them to compare the two games they just played. The questionnaire was presented in a digital form and integrated in the game to rule out any experiment bias introduced by an interviewer [10]. Since the participants had to play more than one game, their physiology signal had to be at baseline level each time they started playing. Therefore, they were instructed by the game to sit down and relax for one minute before playing the next game [11]. The experiment was performed on 33 participants that played two game pairs each, which gave a total of 66 relaxation preferences.

The experiment was performed by using the following procedure: Each of the participants played two game pairs; i.e. four games in total. Prior to the start of the experiment, subjects got a thorough introduction of how to play the game. The time window for each game played was set to 90 seconds. The participants were asked to first play Game A, then Game B and afterwards they were instructed by the game to compare the relaxation felt in the games by answering a questionnaire. The questionnaire uses the 4-alternative forced choice format (1. A > B, 2. B > A, 3. A = B, 4. ¬A ¬ B as suggested in [7]). Only preferences from alternative 1) and 2) were considered valid and were used as training data for the model. The answers from 3) and 4) were given as a alternative choice to provide more expressive freedom for the participants and to eliminate potential biased answers, where a player were forced to have a preference where she has none.

The physiology signal data was gathered from BVP and SC sensors which were attached on the participants' fingertips of the hand that was not moving during gameplay. The rest of the data needed for training the relaxation model were gathered by log files that recorded the data during gameplay.

5. DATA FEATURE EXTRACTION

In total, 62 statistical features were extracted for the physiology signals, the player-game interaction data, and the Wii Remote acceleration data. For the sake of brevity only a small selection of the physiology features are presented in this paper.

The HR signal can be derived from the BVP signal via extrapolation of the inter-beat time intervals. The HR features extracted are: the average HR, $E\{h\}$, the standard deviation of HR, $\sigma\{h\}$, the maximum HR, $max\{h\}$, the minimum HR, $min\{h\}$, the difference between maximum and minimum HR, $D^h = max\{h\} - min\{h\}$, and the approximate entropy $ApEn$ of the signal which quantifies the predictability of fluctuations in the HR time series [7]. The above-mentioned features were extracted from the SC signal as well. Features extracted from the Wii remote motion data include: The average acceleration in x-axis, $E\{a_x\}$, y-axis, $E\{a_y\}$, and z-axis, $E\{a_z\}$, and the average absolute aggregated acceleration in all three axes, $E\{|a_x| + |a_y| + |a_z|\}$. Finally, the following features were extracted from the interaction between the player and the game: player's reaction time from opponent's lightning hit, until the player begins to "shake out" to break the spell: $t^{reaction}$ and the number of gestures performed in the game: $nGestures$.

6. RELAXATION MODEL LEARNING

To construct a relaxation model that predicts the subject's reported relaxation preference a *preference learning* algorithm is used. The assumption is that the player's relaxation value y, which is a response to the game variant, is an unknown function of player specific features can be learned by a machine learning algorithm. Given that both physiology signal data can be noisy and the level of player self reported preference is person-dependent; we believe that ANNs can generate a high-performing and generalising function. A feedforward multilayered ANN for learning the relation between the selected features (ANN inputs) and the relaxation value y (ANN output) is utilised in this paper. Since the output value y is not explicitly defined, normal ANN training algorithms like back-propagation are not applicable. Instead, learning is achieved through artificial evolution.

Neuro-evolutionary preference learning [7], is utilised to construct the computational model of reported relaxation preference. The algorithm uses an evaluation function that measures the difference between the subjects' reported relaxation preferences and the model's output value y. Each member in the population is an ANN with fixed topology (2 hidden layers with 5 neurons each) and the chromosome is a vector of ANN connection weights. The population was initialised with 100 members with random weights [0; 1]. The population reproduces offspring with a crossover rate of 0.75 and mutation rate of 0.25. Elite selection is used as the selection method.

6.1 Feature Selection

In this experiment the *Sequential Forward Selection* (SFS) method was used to automatically select the best feature subset to be used by the ANN model as its input vector. The SFS algorithm is a bottom up search where one feature is added at a time to the current feature subset. The current subset together with each of the remaining features is evaluated with the relaxation model and the best feature is selected and added to the current subset. This is repeated until the added feature yields lower or equal validation performance. In order to evaluate the performance of each feature subset, the performance of the model is evaluated using threefold cross-validation, where the available data is randomly divided into three equal parts. Two of which is used for training and the third is used for validation. The parts are then rearranged and the model is validated again until every part has been used for training and validation.

7. RESULTS

As mentioned before, for the purpose of selecting features, the SFS method is utilised as it is relatively successful in selecting good features. The two controllable game features were enforced to always be a part of the selected feature subset. This was done in order to have a model that can predict the player's relaxation level based on the controllable game features, since these are the features that can be changed to alter the player's relaxation level.

It has been proposed to stop when the added feature yields lower or equal validation performance to ensure minimal subset [12]. In this paper, the algorithm was terminated when an added feature yielded a performance decreased by more than 5% to avoid local minima. The performance of the model is evaluated using threefold cross-validation.

Table 1. Validation performance $P(\%)$ of each iteration of the SFS selection method

SFS	
Feature subset $\{F\}$	$P(\%)$
$\{cu, ch, t^{reaction}\}$	75.99
$\{cu, ch, t^{reaction}, E\{a_x\}\}$	71.15
$\{cu, ch, t^{reaction}, E\{a_x\}, min\{sc\}\}$	**78.42**
$\{cu, ch, t^{reaction}, E\{a_x\}, min\{sc\}, D^h\}$	73.07

As seen in Table 1, $\{cu, ch, t^{reaction}, E\{a_x\}, min\{sc\}\}$ yields a cross-validation performance of 78.42 %. It is interesting to note that the highest performing feature subset selected consists of both SC features and Wii Remote features. When BVP features are added the feature performance falls enough for the selection method to stop. This correlates well with literature that states that SC is a good indication of arousal. The player's reaction time in the game is also a good indicator for relaxation. Possibly a relaxed player has slower reactions than an alert player.

7.1 Wii Remote Features

Because of the wide availability of the Wii Remote, we found it interesting to investigate whether a subset consisting solely of Wii features could give high classification accuracy. As it can be seen in Table 2**Error! Reference source not found.** the model with only Wii Remote features performs closely to the model with access to a full subset of features.

Table 2. Validation performance of the SFS method with subsets restricted exclusively to Wii Remote specific features

SFS	
Feature subset {F}	$P(\%)$
$\{cu, ch, t^{reaction}\}$	**75.99**
$\{cu, ch, t^{reaction}, min\{a_x\}\}$	65.86

7.2 Tailoring Player Experience

With a trained relaxation model that includes controllable game features, it is possible to calculate the network gradient to determine how these features should be adjusted to change the relaxation experienced by the player. A visualisation of this can be seen in Figure 2, where a random subject's (subject 23) input data is used in the relaxation model. In this test game the subject was playing with the controllable features at, challenge: 0.3 and curiosity: 0.3, which is depicted in the figure with a black square. In order to increase the relaxation experienced, the gradient would reveal that the game should increase both challenge and curiosity.

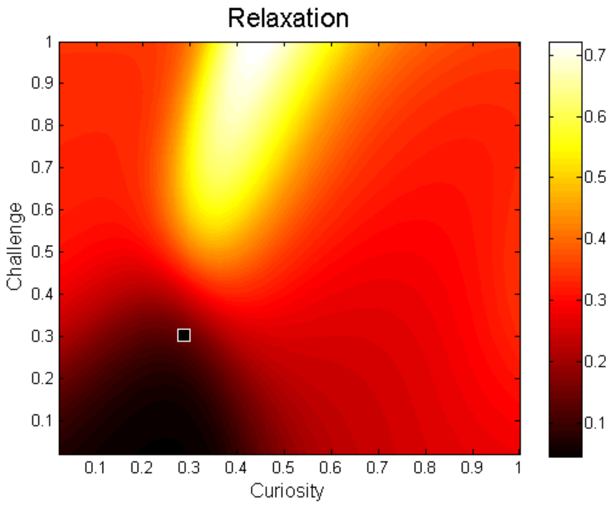

Figure 2. Graph showing the level of relaxation experienced in the game from a fixed subset of features, given the two controllable game features: challenge and curiosity. The squares depict the test subject's placement (challenge = 0.3, curiosity = 0.3)

8. CONCLUSION

This study uses an established methodology for predicting players' relaxation and applies it to a physical Wii game. The methodology was originally applied to playware games [7] and has in other studies been applied to dissimilar games [12] [13] and is in this study applied to a physical Wii game, proving the methodology's scalability. The relaxation model created in this study uses very domain specific game features such as $t^{reaction}$, making the scalability of the model uncertain. The model could possibly be applied in other domains; however, more testing would be needed to verify this. The automated relaxation recogniser achieved a classification accuracy of 78.42% and showed that it could be used to tailor the player experience by calculating the gradients of the curiosity and challenge parameters to ultimately make game design decisions based on these. Furthermore, it was shown that restricting the feature subset to Wii Remote features, the highest classification accuracy achieved was 75.99%. This result is interesting for the game industry as well as in academia as it can be utilised with no need for invasive physiology sensors. However, as physiology sensors are beginning to become more commercial in games e.g. Nintendo's Wii Vitality [14], it is not unimportant to regard physiology features as well, since they can achieve higher classification accuracy.

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11. REFERENCES

[1] Bateman, Chris and Boon, Richard. *21st Century Game Design*. Charles River Media, Inc., Hingham, MA, USA, 2006.

[2] Picard, R. W. *Affective Computing*. MIT Press, Cambridge, MA, 1997.

[3] E. L. Rosenberg, P. Ekman. Emotion: method and study. *Encycllopedia of Psychology*, 3 (2000), 171-175.

[4] Lang, P. J. The emotion probe: Studies of motivation and attention. *American Psychologist* (1995), 372 - 385.

[5] Schachter, S. The interaction of cognitive and physiological determinants of emotional state. *Advances in Experimental Psychology*, 1 (1964), 49-80.

[6] Scherer, K. R. Neuroscience projections to current debates in emotion psychology. *Cognition and emotion*, 7 (1993), 1-41.

[7] Yannakakis, Georgios. N., Hallam, John, and Lund, Henrik H. Entertainment Capture through Heart Rate Activity in Physical Interactive Playgrounds. *User Modeling and User-Adapted Interaction*, 18, 1-2 (Feburary 2008), 207-243.

[8] McQuiggan, Scott W., Lee, Sunyoung, and Lester, James C. *Predicting User Physiological Response for Interactive Environments: An Inductive Approach*. 2006.

[9] Malone, T. W. What makes computer games fun? (1981), 258-277.

[10] Mandryk, Regan L., Inkpen, Kori M., and Calvert, Thomas W. Using psychophysiological techniques to measure user experience with entertainment technologies. *Behaviour and Information Technology (Special Issue on User Experience)* (2006), 141-158.

[11] Mandryk, Regan L., Stella, Atkins, and Inkpen, Kori M. A Continuous and Objective Evaluation of Emotional Experience with Interactive Play Environments. In *CHI 2006 Proceedings - Novel Methods: Emotions, Gestures, Events* (Montréal, QC, Canada 2006), 1027-1036.

[12] Yannakakis, Georgios N. and Hallam, John. Game and Player Feature Selection for Entertainment Capture. In *Proceedings of the 2007 IEEE Symposium on Computational Intelligence and Games* (Hawaii, USA 2007), IEEE, 244-251.

[13] Martinez, Hector. P., Jhala, Arnav, and Yannakakis, Georgios N. Analyzing the Impact of Camera Viewpoint on Player Psychophysiology. In *Inernational Conference on Affective Computing and Intelligent Interaction (ACII'09)* (Amsterdam, The Netherlands September 2009).

[14] Pedersen, Christoffer, Togelius, J., and Yannakakis, Georgios N. Modeling Player Experience in Super Mario Bros. In *Proceedings of the IEEE Symposium on Computational Intelligence and Games* (Milan September, 2009).

[15] *Nintendo : E3 2009 : Press Release*. 2009.