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GamEMO: How Physiological Signals Show your Emotions and Enhance your Game Experience

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ABSTRACT

The proposed demonstration is an automatic emotion assessment installation used for game's dynamic difficulty adjustment. The goal of the system is to maintain the player of the game in a state of entertainment and engagement where his/her skills match the difficulty level of the game. The player's physiological signals are recorded while playing a Tetris game and signal processing, feature extraction and classification techniques are applied to the signals in order to detect when the player is anxious or bored. The level of the Tetris game is then adjusted according to the player's detected emotional state. The demonstration will also serve as an experimental protocol to test the player's experience through their interaction with the proposed platform.

Categories and Subject Descriptors

D.3.3 [Programming Languages]: Python, I.5.4 [Applications]: Signal processing, K.8.0 [General]: Games

Keywords

Affective Computing, Games, Emotion Assessment, Physiological Signal Processing, Pattern Recognition, Classification.

1. INTRODUCTION

Computer game experience can be described as joyful and entertaining, though it can sometimes produce negative feelings as anxiety or boredom. Certainly, it elicits various feelings to players that can be taken into consideration in order to enhance the gaming experience. For instance it seems that different game difficulty levels correspond to distinguishable emotions [1]. According to emotion and flow theories [3], [4] strong involvement in a task occurs when the skills of an individual meet the challenge of a task (Fig. 1). Too much challenge would raise anxiety and not enough would induce boredom. Affective computing [7] along with multimodal interaction has opened a new path in human-computer interaction (HCI) where machine's behavior is adjusted dynamically to user's affective cues. It follows that entertainment and engagement of players, as being the main goals of a game, can be achieved through automatic adjustment of a game's level according to user's emotional feedback: the difficulty of the game should be lowered when the player is anxious and increased when the player is bored.

According to [6], a dynamic difficulty adjustment affective

computer game can enhance the gaming experience by making it less stressful and more challenging.

Emotions can be detected through measurements of the peripheral nervous system activity (e.g., heart rate, electrodermal activity-EDA, Blood Volume Pulse- BVP). Evidence for emotion's detection through peripheral signals and its use in affective computing can be given from several studies in the literature [1], [2], [5], [6], [7], [8]. The challenge is to compute and then classify multimodal physiological features into given emotional states with a sufficient accuracy.

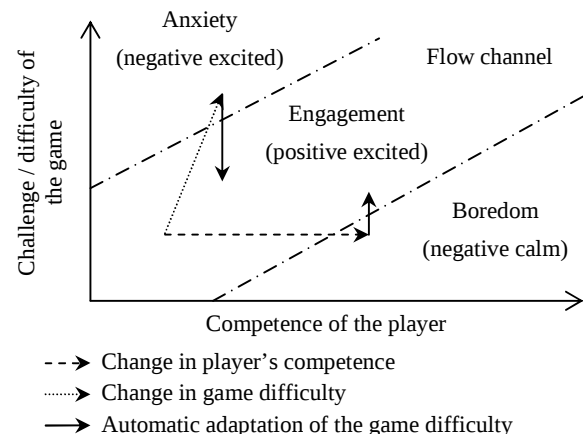


Figure 1: Flow chart and the suggested automatic adaptation to emotional reactions [1].

In the current study, automatic emotion assessment through several peripheral signals is implemented in order to provide emotional feedback to the computer game (Tetris) and adapt the difficulty level of the game (speed of the falling blocks). In this way the considered emotional states, anxiety and boredom are used to automatically adjust the Tetris level to the player's skills.

2. SYSTEM

2.1 System's Description

2.1.1 Game Player (P)

The player (P) is seated in front of the computer G (Fig. 2). In his disposal there are a keyboard and a screen that are used to play the Tetris game. While interacting with the game, P's peripheral physiological signals (ElectroDermal Activity - EDA, Blood Volume Pulse - BVP, Skin Temperature and Chest Cavity

Expansion) are continuously recorded from his non-dominant hand and his chest. P is thus able to play Tetris with his dominant hand using the keyboard.

2.1.2 Amplifier Box (B) & Data Acquisition Computer (A)

The peripheral electrodes are connected to the ActiveTwo AD-box from Biosemi™ (B) (Fig. 2). B is used to convert the analog recorded signals to digital signals and to send the data, via an optical fiber, guaranteeing player's galvanic isolation, to the data acquisition computer (A) (Fig. 2). The signal acquisition program (Actiview™) is installed on computer A and is used for displaying the physiological signals and sending the physiological data via TCP/IP connection to the main computer (G) (Fig. 2).

2.1.3 Gaming and Processing Computer (G)

This computer is situated in front of P and is used in the current installation for the following reasons:

- interaction of the player with the game;
- multimodal signals processing;
- classification of player's emotional state;
- adjustment of Tetris difficulty level according to the detected emotion.

The Tetris game is an adapted installation of DotNETris implementing 25 difficulty levels modulated by the speed of the falling blocks (one block going down a line every 0.54 s at level 1 and every 0.003 s for level 25). The game is played by using the arrows of the keyboard.

The signal's processing and the classification are implemented with modules written in Python. Before starting the processing and the classification, the system need to be calibrated by recording a one minute baseline with the player staying relaxed. Once the baseline is recorded the signal processing and classification systems are executed together with the game. The system always uses the last minute of recorded physiological activity to infer the emotional state of the player. In consequence the first estimation can only be given after one minute of playing after which the system gives an estimate every 30 seconds.

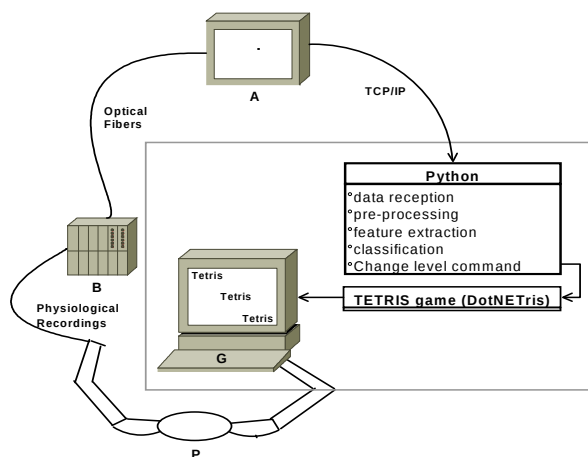


Figure 2: System's Installation Schema: A: Data Acquisition Computer, B: Amplifier G: Main computer, P: Game Player

The first processing step is the data reception through TCP/IP connection and buffering in a one minute data buffer. Then all

physiological data are pre-processed through filtering and referencing. Heart rate is computed from the BVP signal. Feature extraction is then required to characterize player's physiological states. Six features were chosen based on our previous study [1]: average temperature, average heart rate, average EDA, the duration of decreasing EDA over the recording period, the number of peaks in the EDA signal and chest expansion standard deviation. A Linear Discriminant Analysis (LDA) classifier is trained on the data collected in [1] and is then applied to the on-line extracted features in order to determine the current emotional state of the player among boredom and anxiety. The last step is to adjust game's level to player's current state. Detection of anxiety leads to the decrease of one game level and detection of boredom to an increase of one game level.

3. TESTING PROTOCOL

In order to test the present installation, participants will be asked to sit in front of the demonstration computer. They will be equipped with 5 recording electrodes at their non-dominant hand for referencing, EDA and temperature measurements. A BVP sensor will be clipped around the thumb of the same hand and one respiration belt will be tied around their abdomen. They will be asked to stay calm and relaxed for at least 1 min in order to record the baseline activity and then they will start playing the game. The game will be adjusted by the experimenter and some of the participants will start with the high difficulty level and some other from the low difficulty level. Affective game experience will be evaluated at the end of the demo session with a questionnaire.

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