Identifying Psychophysiological Correlates of Boredom and Negative Mood Induced During HCI

Dimitris Giakoumis[1, 3], Athanasios Vogiannou[1, 3], Illka Kosunen[2]
Kostantinos Moustakas[1], Dimitrios Tzovaras[1] and George Hassapis[3]

[1]Centre for Research and Technology Hellas, Informatics and Telematics Institute
6th Km Charilaou-Thermi Road Rd., 57001, Thermi, Thessaloniki, Greece
{dgiakoum,tvog,moustak,tzovaras}@iti.gr
[2]Helsinki Institute for Information Technology, Pilotti Building
Metsδnneidonkuja 4, 02100 Espoo, Finland
ilkka.kosunen@hiit.fi
[3]Aristotle University of Thessaloniki
Department of Electrical and Computer Engineering, Greece
ghass@auth.gr

Abstract. This paper presents work conducted towards the automatic recognition of negative emotions like boredom and frustration, induced due to the subject's loss of interest during HCI. Focus was on the basic pre-requisite for the future development of systems utilizing an "affective loop", namely effective recognition of the human affective state. Based on the concept of "repetition that causes loss of interest", an experiment for the monitoring and analysis of biosignals during repetitive HCI tasks was deployed. During this experiment, subjects were asked to play a simple labyrinth-based 3D video game repeatedly, while biosignals from different modalities were monitored. Twenty one different subjects participated in the experiment, allowing for a rich biosignals database to be populated. Statistically significant correlations were identified between features extracted from two of the modalities used in the experiment (ECG and GSR) and the actual affective state of the subjects.

1 Introduction

The development of automatic affect recognition systems based on biosignals has attracted much attention recently. The Jamesian theory [1] emphasizes the importance of peripheral signals in affect recognition, as it suggests there are specific patterns of physiology that relate to different emotions. During the last years, several important attempts have been made towards this direction; e.g. [2], [3], [4], [5], [6], [7], underlining the usefulness of peripheral activity for emotion assessment in diverse conditions.

The potential development of future game-playing systems which, based on an affective loop [8], will be able to adapt on the basis of the player's emotions seems very interesting. Such systems will be able to identify whether the player is getting bored of the game and then adapt the playing context accordingly, in order to draw her/his attention again and induce more positive emotions. The first step towards this direc-

tion is the development of appropriate classifiers, able to effectively identify the user's affective state of boredom, induced while playing. Previous work [9] has already shown that playing simple games like Tetris at different levels of difficulty gives rise to different emotional states that can be defined as boredom, engagement and anxiety. That specific work aimed at the automatic recognition of the player's state of boredom from biosignal features; the desired emotional states were induced by playing Tetris game versions of different difficulty.

Moving towards more typical game-playing scenarios, in this work we focus on the identification of the most appropriate biosignal features to use for the effective classification of negative emotions like boredom and frustration, during playing typical 3D video-games. For this purpose, we have examined a set of features extracted from various biosignal modalities monitored during a negative emotion-induction experiment, based on repetitive playing of a 3D Labyrinth game. The aim of this analysis (Fig. 1) was to identify correlations between the extracted biosignal features and the actual affective state of the player, as the latter changed during the experimental session. For the purpose of the experiment, data was collected from four different biosignal modalities (EEG, ECG, GSR and EMG). However, since the data analysis is a work in progress, in this paper we focus on the two modalities that have until now produced the most significant correlations to the ground truth data, namely ECG and GSR.

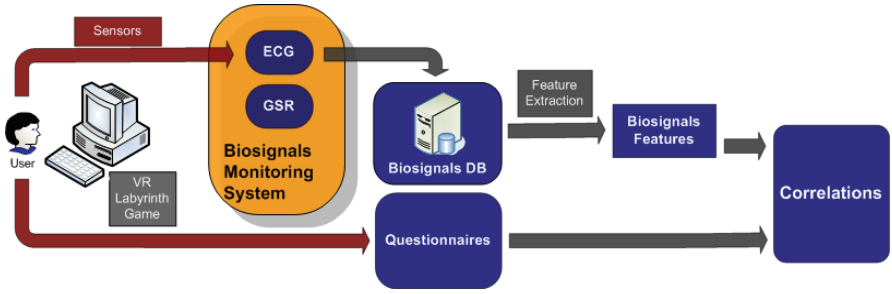


Fig. 1. Overview of Experiment and Data Analysis presented in this paper.

In the following of this paper, the monitoring framework's background is provided in Section 2, followed by the description of the methods used for feature extraction regarding each modality (Section 3). The experiment conducted for data collection is presented in Section 4. Finally, Section 5 presents statistically significant results from the analysis of the data collected, followed by conclusions, presented in Section 6.

2 Monitoring Framework Background

In this work, Electrocardiogram was used in order to assess the subject's Heart Rate Variability (HRV). HRV describes the variations between consecutive heartbeats. The regulation mechanisms of HRV originate from the sympathetic and parasympathetic nervous systems and thus HRV can be used as a quantitative marker of the autonomic nervous system's operation [10]. Features extracted from ECG, reflecting

the subject's HRV have already been used together with features derived from other modalities in a number of studies targeting automatic emotion recognition e.g. [3], [4], [5], [6], [11]. Most commonly used HRV analysis methods are based on the time and frequency domains [12].

Time-domain HRV parameters are the simplest ones, calculated directly from the RR interval (or Inter-Beat Intervals) time series. These are the time series produced from the time intervals between the consecutive "R-peaks" of the raw ECG signal. The simplest time domain measures are the Mean and Standard Deviation of the IBIs. Commonly used HRV features are also the RMS of the IBI Sequential Differences (RMSSD) and the percentage within a time period of sequential differences that are over 50 milliseconds (pNN50). These features provide additional information about large-amplitude beat-to-beat changes in HR. In the frequency-domain analysis, power spectral density (PSD) of the IBI series is usually calculated. The commonly used frequency bands for HRV are Very Low Frequency (VLF, 0-0.04 Hz), Low Frequency (LF, 0.04-0.15 Hz), and High Frequency (HF, 0.15-0.4 Hz). The most common frequency-domain HRV features include the powers of VLF, LF, and HF bands and the LF to HF ratio.

Galvanic Skin Response (GSR), also referred to as Electrodermal activity (EDA), is a measure of skin conductance, which can be seen as an indirect measure of sympathetic nervous system activity [13]. The outer level of skin is highly resistive while the deeper layers of skin are highly conductive. These levels are "connected" by sweat glands, that when opened, create a pathway from the surface of the skin to the deeper, conductive level of the skin [14]. There are two main types of fluctuations of EDA that occur with stimulation: the momentary phasic responses and the more stable tonic level. Both phasic and tonic GSR features are commonly used towards automatic affect recognition [2], [3], [4], [5], [6], [11], [15]. GSR features commonly extracted and used in the literature are the Mean level of the GSR signal and the skin conductivity startle responses (Skin Conductance Response - SCR). SCRs are distinctive short waveforms (for a description see [4]) found inside the GSR signal that signify responses to internal or external stimuli.

3 Feature Extraction

In an effort to identify the best features to use for the development of proper classifiers regarding our specific application scenario, various features were extracted from the recorded signals and analyzed. The features used in the present analysis were checked for robustness to potential noise that could appear in the recorded signals.

Regarding the ECG modality, we considered the extraction of features from the subject's Inter Beat Intervals (IBI) time series. ECG data were collected at a sampling rate of 256 Hz. Inter-Beat Intervals were calculated from the subject's recorded Electrocardiogram, directly by our monitoring device's (Procomp5) software. Prior to feature extraction, IBI artifacts were removed by a filter excluding IBIs over 1200 and under 500 ms. This filtering was applied in order to exclude IBI values which could not be normal, given our specific application scenario. Thresholds were set at

the values 500 and 1200 ms since an IBI outside this range would mean that the subject suddenly had a Heart Rate over 120 or under 50 beats/minute respectively.

Table 1. Features extracted from the Inter Beat Intervals time series of the ECG modality.

Feature Name	*Formula*	*Description*
IBI Mean per trial	$ibi_{mean} = \frac{1}{n}\sum_{i=1}^{n} ibi_i$ n = number of IBIs during the trial	The average duration of the Inter-Beat Intervals during each trial
IBI SD per trial	$ibi_{SD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ibi_i - ibi_{mean})^2}$	The Inter Beat Intervals Standard Deviation during a trial
IBI LF/HF per Trial	$ibi_{LHm} = \frac{\sum_{i=1}^{n} lfp_i}{\sum_{i=1}^{n} hfp_i}$ lfp_i = Low Frequency band power hfp_i = High Frequency band power	The average ratio of the Low Frequency band power to the High Frequency band power during a trial
IBI RMSSD	$ibi_{SD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ibi_{i+1} - ibi_i)^2}$ $\forall(ibi_{i+1} - ibi_i) \neq 0$	RMS of the sequential differences of the IBI calculated for the whole trial
IBI pNN50	$ibi_{pNN50} = \frac{nd_{>50}}{nd}$ $nd_{>50}$ = number of sequential IBI differences that are over 50 ms within a trial nd = total number of sequential differences during the trial	Percentage of the number of sequential IBI differences that are over 50 ms

The time-domain (TD) and frequency-domain (FD) features shown in Table 1 were extracted from the IBI time series:

Regarding the GSR modality, we examined both the tonic and phasic electrodermal activity. The following features were extracted from the recorded GSR signals, sampled at a rate of 256 Hz:

The average value of the GSR signal during each trial (feature **GSR Mean** per Trial) was calculated with the formula:

$$gsr_{mean} = \frac{1}{n}\sum_{i=1}^{n} gsr_i \tag{1}$$

Where n = Total number of GSR samples during the trial

For the extraction of features related to the phasic electrodermal activity the subject's Skin Conductance Responses (SCRs) during each trial were identified. Due to

the fact that the majority of trials were about half minute long, only the first twenty five seconds of each trial were taken into account for the identification of SCR occurrences. Initially, the 1st derivative of the GSR signal values was calculated:

$$gsr\_d1raw_i = \frac{gsr_{i+1} - gsr_i}{t_{i+1} - t_i}. \quad (2)$$

Where gsr_i = Value of the i^{th} GSR sample, t_i= Timestamp of the i^{th} GSR sample

The resulting time-series was convoluted with a 255-point Bartlett window. As a result, the time series of the smoothed GSR 1st derivative values, *gsr_d1* was produced. Similarly to the procedure applied in [4], the occurrence of an SCR was detected by finding two consecutive zero crossings, from negative to positive and from positive to negative within the time series of the GSR smoothed first derivative (*gsr_d1)*. The maximum amplitude of the detected SCR was obtained by finding the maximum value of the actual GSR signal between these two zero-crossings. Detected SCRs with maximum amplitude smaller than the 10% of the maximum SCR amplitude detected within each trial were excluded. After all SCRs were identified, together with their maximum amplitude and duration, the features **Number of SCRs**, **Average Amplitude of SCRs** and **Average Duration of SCRs** were calculated for the first 25 seconds of each trial. The average value of the smoothed GSR first derivative (*gsr_d1)* per trial was also extracted as feature (**GSR 1st Derivative**).

In order to perform proper group analysis, between-subject normalization was applied to the data collected from the ECG and GSR modalities, following two different normalization methods: The first method (N1) produced the ratio of each feature to its value obtained from the rest period of the specific subject. The second method (N2) was based on the transformation of each sample into a percentage of the span for that particular signal, similarly to the procedure applied in [16]: For each signal (GSR and IBI), a global minimum (x_{min}) and maximum (x_{max}) were obtained for each participant using all game playing trials, and the same global values were used for normalizing each sample of the specific signal within each trial with the formula:

$$x_{N2}(i) = \frac{x(i) - x_{min}}{x_{max} - x_{min}}. \quad (3)$$

Where x = Samples of the GSR or IBI signals, x_{N2} = Normalized samples of the GSR or IBI signals

4 Experimental Setup

The aim of the experiment was to monitor the subject's biosignals while the state of boredom due to loss of interest was induced from a repetitive HCI task, namely the repetitive playing of the same 3D Labyrinth game. The subject's actual affective state during the experimental session was assessed with the use of questionnaires, filled in after each trial.

4.1 Stimuli

A basic 3D labyrinth game (Fig. 2) was developed for the purpose of the experiment. In order to complete the game, the players had simply to find the exit. The player could walk through the mazy corridors of the labyrinth using a 3D first person camera which is controlled by the WASD/Arrow keys and the mouse, a standard method used in commercial games. The game was developed in C++ using OGRE (http://www.ogre3d.org/) for graphics and the "Bullet" physics library (http://www.bulletphysics.com) for physics simulation. The tests were performed on a Laptop PC with an Intel Core 2 Duo T7700@2.40GHz CPU, 2 GBs of RAM and a NVIDIA GeForce 8600M GT graphics card. The game ran steadily on a 60 frame/sec rate.

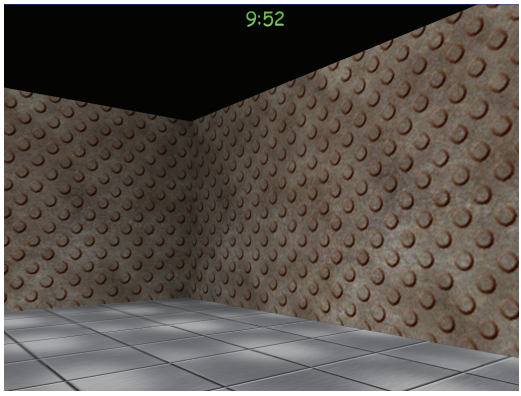
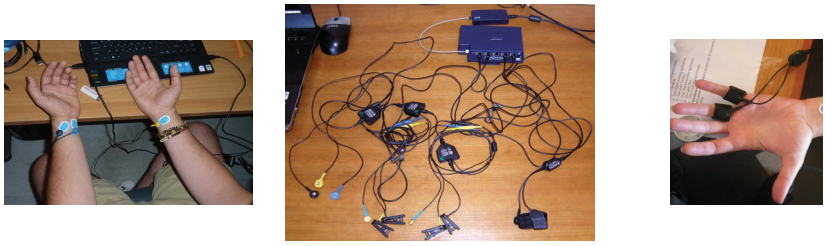


Fig. 2. Screenshot of the VR Labyrinth game.

In order to induce drowsiness due to loss of interest effectively, the Labyrinth was designed to be a very simple one. Furthermore, in all repetitions the player started from the same point and the Labyrinth exit was always at the same place. Usually, after the third or fourth trial, the subject had learnt the shortest path to the exit. Thus, even though in the beginning (first two trials), the game was kind of exciting, as soon as the subject had learned the shortest path to the exit, the stimuli became an absolutely repetitive HCI task, ideal to induce negative emotions (e.g. boredom) due to loss of interest.

4.2 Hardware Setup

Both ECG and GSR biosignals were recorded using a Procomp5 Infiniti device (**Fig. 3**b)**.** One three-electrode ECG sensor was placed at the subject's forearms, or in cases that the subject had very low cardiac pressure, on its chest (Fig. 3a). Autoadhesive Ag/AgCl bipolar surface electrodes (bandwidth 10-500 Hz, pickup surface 0.8 cm2, inter-electrode distance 2 cm) were used for the ECG signal acquisition. Furthermore, one two-electrode GSR sensor placed at the subject's left hand ring and small fingers (Fig 3c). The synchronization of the measurements and the VR Labyrinth game was based on a custom-made application, using the Network Time Protocol (NTP).



(a) (b) (c)

Fig. 3. Experimental Setup: (a) ECG sensors, (b) the Biosignals Monitoring Device and (c) GSR sensors.

4.3 Participants and Procedure

The experiment was performed with twenty one subjects chosen among the participants of the eNTERFACE'09 summer workshop held in Genova, Italy. All participants frequently used computers in their work and were between 23 and 44 years old with 48 percent of them being 25 and 26 years old, 14 were males and 7 females. Forty two percent of the subjects were already familiar with 3D maze games but only nineteen percent of them played this type of game frequently (more than one hour per week). Trials from four different subjects were excluded from data analysis due to artifacts.

Initially, the subjects were asked to sign a consent form. After that, the sensors were installed, while the subject answered questions regarding personal details and previous gaming experience in the pre-questionnaire. At this point, the proper sensor placement was ensured, by checking carefully the robustness of the signal delivered from each monitoring modality. The recorded signals were checked on line for artifacts due to external noise or mechanical causes (e.g subject's motion). The preparation was renewed when severe artifacts were observed.

Once the sensors were properly placed, the subject was asked to relax with eyes-closed for one minute in order for the signal to stabilize and calibration data to be recorded (rest period). After the end of the rest period, the VR Labyrinth game was presented to the subject. From this point, the subject would play the Labyrinth game repeatedly. Each experimental session constituted of at least ten trials. Each trial started when the subject started playing the Labyrinth game and stopped as soon as the subject had found the exit, or a 10 minute time-limit had expired. Trials usually lasted from half to eight minutes. A mid-trial relaxation period of one minute was assigned between each trial. During this period, subjects had to fill in the mid-trials questionnaire. Using a Likert scale ranging from 1 to 5, they had to answer whether they would like to play the Labyrinth game again, whether they felt frustrated or bored of it and whether they were concentrated during the trial or focused on external events and/or personal thoughts. The experiment continued until the subjects had

played a minimum of ten trials and had signaled drowsiness/boredom in the questionnaire at least two times in a row. At the end of the experiment, subjects were asked to fill in a post-questionnaire, which was used for the assessment of their overall level of immersion during the entire experiment. Additional stages were also included in the experimental protocol; however these did not interfere with the induction of boredom and are outside the scope of the data analysis presented in this paper.

5 Results

In order to identify correlations between biosignal features and the subject's actual affective state, we followed an analysis based on the Kendall's tau correlation coefficient. In particular, the correlation between the subject's Likert-scaled answers to specific questions of the mid-trial questionnaires, and each of the features extracted from the biosignals was calculated. Significance level was set at p=0.05 (*) and p=0.01(**). Questions considered in this analysis assessed the player's tendency to stop playing the game (Q1), frustration (Q2) and boredom (Q3). Furthermore, we considered two more questions, assessing factors of the player's affective state which can be thought opposite to boredom, like the player's level of immersion/flow (Q4) and concentration (Q5). Several statistically significant correlations were identified and are summarized in Table 2.

Table 2. Statistically significant correlations of Features extracted from the ECG and GSR modalities (N=Number of cases).

Question	***Feature***	***Correlation (Kendall's tau)***		
Q1	**IBI Mean** per trial (N2)	τ=-0.284**	p<0.001	N=221
(Play again)	**Number of SCRs** per trial	τ= 0.133*	p=0.014	N=221
Q2	**IBI Mean** per trial (N2)	τ= 0.120*	p=0.019	N=221
(Frustration)	**IBI LF/HF** per Trial (N1)	τ= 0.104*	p=0.042	N=221
	GSR Mean per trial (N2)	τ= 0.193**	p<0.001	N=221
Q3	**IBI Mean** per trial (N2)	τ= 0.258**	p<0.001	N=221
(Boredom)	**IBI RMSSD** per trial (N1)	τ=-0.103*	p=0.040	N=221
	Number of SCRs per trial	τ=-0.199**	p<0.001	N=221
	GSR 1st Derivative per trial	τ=-0.166**	P<0.001	N=221
Q4	**IBI SD** per trial (N1)	τ= 0.209**	p<0.001	N=221
(Flow / Immersion)	**IBI LF/HF** per Trial (N1)	τ= 0.100*	p=0.045	N=221
	IBI RMSSD per trial (N1)	τ= 0.165**	p=0.001	N=221
	IBI pNN50 per trial (N1)	τ= 0.104*	p=0.048	N=199
Q5	**IBI Mean** per trial (N2)	τ=-0.176**	p=0.001	N=187
(Concentration)	**IBI SD** per trial (N1)	τ= 0.155**	p=0.004	N=187
	IBI RMSSD per trial (N1)	τ= 0.125*	p=0.020	N=187

Frustration (Q2), boredom (Q3) and a tendency to stop playing the game (Q1 inversed) were found to correlate positively to the IBI Mean per trial feature. This indi-

cates a tendency of the subject's Heart Rate to decrease, when a negative mood is induced from the interaction. Furthermore, frustration was also found to correlate to the LF to HF Average Ratio per trial and the Average value of the subject's GSR signal per trial (τ= 0.193, $p<0.001$). These features are indicative of the subject's sympathetic nervous system activation and thus, her/his overall level of arousal, which is expected to increase with frustration. Boredom was found to correlate negatively to the subject's number of SCRs per trial (τ=-0.199, $p<0.001$), in accordance to the fact that increased numbers of SCRs are connected to higher levels of arousal. Furthermore, boredom was also found to correlate negatively to the average value of the GSR first derivative per trial (τ=-0.166, $p<0.001$).

Regarding the questions assessing factors opposed to boredom, flow and immersion was found to positively correlate to the IBI Standard Deviation, LF to HF Average Ratio, RMSSD and pNN50, features connected to higher levels of immersion and arousal. Finally, concentration correlated positively to the subject's Heart Rate (Inverse of IBI Mean), and negatively to the IBI Standard Deviation and RMS of Sequential Differences. The GSR Mean per trial feature correlated negatively (τ=-0.203, $p<0.001$) to the subject's concentration level.

Summarizing, several features extracted from ECG and GSR biosignals were found to correlate significantly to the subject's actual affective state during the experimental session. These identified correlations could be used in the future as a guide for effective feature selection towards automatic emotion recognition, although the Kendall correlation coefficient did not reach very high values (up to ~0.25) in general. The EEG and EMG modalities used in the experiment have not produced equally significant results until now; however we strongly believe that more sophisticated preprocessing, analysis and fusion of all monitored modalities can lead to better results in the future.

6 Conclusions

This work presents a biosignals-based experiment, which focused on the identification of psychophysiological correlates of the changes in the user's affective state during repetitive tasks in HCI. Data was collected from 21 subjects who played the same video game repeatedly, while their EEG, EMG, ECG and GSR signals were recorded. Various features were extracted from the biosignals and examined with the aim to identify statistically significant correlations between them and various Likert-scaled questions assessing the player's affective state. The analysis was based on the Kendall's tau correlation coefficient.

Various features extracted from ECG and GSR biosignal modalities were analyzed, so as to identify significant ones that could be used in the future for the automatic classification of negative emotions and mood, induced during 3D video-game playing. This work is planned to continue working towards the development of classifiers for the effective recognition of boredom, induced due to the player's loss of interest. The major future goal is the development of a real-time monitoring framework for affective state classification, towards the realization of Human-Machine Interfaces based on affective loops.

References

1. Cornelius, R.R., 1996. The Science of Emotion. Prentice-Hall, Upper Saddle River, NJ
2. Picard, R. W., Vyzas, E., and Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. IEEE Transactions on Pattern Analysis and Machine Intelligence, 23(10),1175-1191
3. Kim, J. and Andr´e, E. (2008). Emotion recognition based on physiological changes in music listening. IEEE Transactions on Pattern Analysis Machine Intelligence, 30(12):2067–2083
4. K. H. Kim, S. W. Bang, and S. R. Kim, "Emotion recognition system using short-term monitoring of physiological signals" Medical & Biological Engineering & Computing, vol. 42, pp. 419-427, May 2004
5. Wagner, J.,Kim, J.,Andre´, E. , 2005. From physiological signals to emotions: implementing and comparing selected methods for features extraction and classification. In: IEEE International Conference on Multimedia & Expo
6. Haag, A., Goronzy, S., Schaich, P., Williams, J., 2004. Emotion recognition using biosensors: first step toward an automatic system. In: Affective Dialog Systems: Tutorial and Research Workshop, Kloster Irsee, Germany
7. M. Benovoy, J. R. Cooperstock, and J. Deitcher. Biosignals analysis and its application in a performance setting - towards the development of an emotional-imaging generator. In P. Encarnação and A. Veloso, editors, BIOSIGNALS (1), pages 253–258. INSTICC, 2008
8. Sundström, P. (2005), Exploring the Affective Loop, PhD thesis, Stockholm University
9. Chanel, G.,Rebetez,C.,Be´trancourt, M.,Pun,T.,2008. Boredom, engagement and anxiety as indicators for adaptation to difficulty in games. In: 12th International Mind Trek Conference: Entertainment and Media in the Ubiquitous Era. ACM, Tampere, Finland
10. Task force of the European society of cardiology and the North American society of pacing and electrophysiology. Heart rate variability – standards of measurement, physiological interpretation, and clinical use. Circulation, 93(5):1043–1065, March 1996
11. Rainville, P., Bechara, A., Naqvi, N., Damasio, A.R., 2006. Basic emotions are associated with distinct patterns of cardiorespiratory activity. International Journal of Psychophysiology 61 (1), 5–18
12. G.G. Berntson, J.T. Bigger Jr., D.L. Eckberg, P. Grossman, P.G. Kaufmann, M. Malik, H.N. Nagaraja, S.W. Porges, J.P. Saul, P.H. Stone, and M.W. Van Der Molen. Heart rate variability: Origins, methods, and interpretive caveats. Psychophysiol, 34:623–648, 1997
13. Andreassi, J. L. (1995). Psychophysiology: human behavior and physiological response. Hillsdale, N.J., Lawrence Erlbaum Associates
14. Schwartz, M. S. (1995). Biofeedback: A Practioner's Guide. New York: Guilford Press
15. Chanel, G., Kronegg, J., Grandjean, D., Pun, T., 2006. Emotion assessment: arousal evaluation using EEG's and peripheral physiolo- gical signals. In: Gunsel, B., Tekalp, A.M., Jain, A.K., Sankur, B. (Eds.), Multimedia Content Representation Classification and Security. Springer Lecture Notes in Computer Sciences, vol. 4105, pp. 530–537.
16. Mandryk, R. L., & Atkins, M. S. (2007). A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. International Journal of Human-Computer Studies, 65, 329-347