A rough BCI-based Assessment of User's Emotions for Interface Adaptation: Application to a 3D-Virtual-Environment Exploration Task

Valeria Carofiglio[1], Fabio Abbattista[1]
[1] Department of Computer Science, University of Bari, Via Orabona 4, 70124 Bari, Italy

Abstract. In order to develop an Adaptive Virtual Environment (AVE), users' experience, their needs and preferences should be accounted. In the methodology we presented in this paper, to build a 3D Adaptive Virtual environment (AVE), we overcome the weaknesses of user-centered evaluation (UCE) traditional methods by employing a Brain Computer Interface (BCI): The proposed methodology aims at (I) supporting the design of an engaging overall experience for potential users, (II) enhancing the user experience by dynamically adapting the interaction to the user emotional state so that a more immersive interaction could result.

1 Introduction

In order to build systems that acquire information about users so as to adapt their behavior to each one of these users, the new interaction paradigms encourage to explore new variables for accounting the user experience [1]. In this context, a good application design should manage also the user's emotional level so that a system can more effectively adapt to the user. In this paper a 3D virtual environment (3DVE) is described as elicitors of complex user emotion synthesis, but also as one of the most representative examples of emotional Adaptive virtual environment, in which the more the system knows about the user's detailed emotions, the better it can react by guiding the user along a well-defined emotional and informative paths.

Due to their ability to retrieve emotional activity of a subject [2]-[4] beyond his conscious and controllable behaviors and in a transparent manner, we employed brain computer interfaces (BCIs, [5]), both in affective detection and modelling phases. In a general view, a BCI is a direct communication pathway between the brain and an external device. By means of electroencephalogram (EEG), it records human brain activity, through multiple electrodes that are placed on the scalp. Human brain activity is processed to obtain features that can be grouped into a features vector: Depending on the brain activity, distinctive known patterns in the EEG appear. These are automatically recognized by the BCI, and associated with a given action on the BCI application. The outcome of the user's action can be perceived by the user himself in terms of application's feedback. In this case his brain activity is consequently modulated. To account for user emotional state during BCI operations, most of the literature suggests an exhaustive training of the BCI classification algorithm under various emotional stimulations. If a passive BCI [6] is employed, active user involvement is not required and the interpretation of his mental state could be a source of control to the automatic system adaptation, for example in order to motivate and involve him by the application feedback.

Many authors have investigated the use of physiological methods to detect and recognize users' emotional state. In [7] authors reviewed many psychophysiological measures applied to the game research and their potential effectiveness in order to better understand the gaming experience and the design of more engaging games.

Lisetti et al, in [8] used noninvasive tools to acquire physiological signals from users. Their goal was to provide a mapping between several physiological signals and users' emotions. By using machine learning techniques they were able to recognize users' emotion with a quite good accuracy.

Our research's main goal includes two topics of investigation: (I) How emotional user experience may be evaluated: This is linked to the possibility of implementing a highly portable and low-cost BCI that is able to efficiently recognize emotions from the EEG signals. (II) How the outcome of this evaluation can be used to enhance emotional user experience. The expected result is a dynamic increase of the interaction's customization and therefore an improvement of the user's satisfaction, focusing on how self-induced emotions [9] could be utilized in a BCI paradigm (real-time data processing). In this view, the real-time acquisition of information about the emotional state of the user provided by the system should be used to adapt the characteristics of the interaction: That should give the chance of better reaching the intended emotional effects on each individual user. In [10], authors used some physiological signals to adapt the difficulty of the tetris game to the emotional response from the player. Their results show that EEG signals are more accurate than other measures such as peripheral signals

In the scope of this paper, we focused on (II): To our aim, we firstly focused on the design of an immersive overall experience for potential users, by exploiting their emotional level as powerful engine in the interaction experience: We extend the work we conducted in [11]. We secondly worked at enhance the user experience by dynamically adapting the interaction to the user emotional state [12], [13], so that a more immersive interaction could result. In this paper, the phases of emotion elicitation and affect driven system adaptation are detailed. We decided to use a commercial BCI, and its proprietary sdk and algorithms, in the affective detection and modeling phases (see section "4 Emotional User Experience Recognition by Emotiv™ Epoc"). Nevertheless, a further study with more professional EEG hardware will be our concern.

2 The Adaptive 3D Virtual Environment

In [11] we detailed a pilot study which was conducted for determining if the contents of a given 3DVE could result in high subject agreement in terms of elicited emotion. The experimental environment was chosen among the applications requiring detection and management of user's emotions to provide an appropriate user experience. As main example of this kind of application, we considered a 3D reconstruction of part of a Nazi extermination camp, such as Auschwitz. In the 3DVE (Fig. 1), a digital character representing a prisoner guides users through different parts of the camp. During the navigation, the 3DVE activates links to videos and photos documenting the Jewish and Gipsy's lifestyle in the 1940-1945 period, or plays songs that some prisoners composed during their permanence.

In this first release, the environment included 8 different scenes; among these, six scenes contain historical multimedia documentation; the remaining two included only the 3D reconstruction of the camp. In choosing multimedia contents, we avoided scenes that could objectively induce psychological harm.

By means of the BCI (the virtual environment has been interfaced with the Emotiv™ Epoc headset http://www.emotiv.com), we captured the user' reaction to presented contents in order to evaluate: (I) how much the 3D environment was inherently emotive, (II) how much each scene contributed to the inherent emotional level of the 3D environment and (III) how much the multimedia content of each scene contributes to the emotional response with respect to the scenes not enriched with multimedia contents.

Both instantaneous (IE) and long term (LTE) excitement detected by the headset (for more detail about IE and LTE, see section 4), together with the emotions felt by the users (as declared in the questionnaire) has been employed as measure to evaluate the previous factors.

According to the experimental results presented in [11], we redesigned the 3DVE, in order to enclose to it more multimedia contents (historical multimedia documentation and several virtual elements). All of the multimedia contents included in the new 3DVE have been previously classified in terms of the emotional impression possibly induced in an observer: 5 subjects participated in this classification task. Each of them observed the elements one by one.

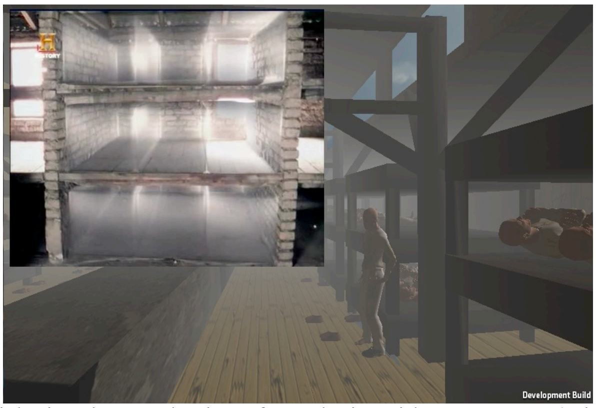


Fig. 1. Partial Virtual Reproduction of Auschwitz-Birkenau – BIIB (prisoner's barracks). The 3D Virtual environment is enriched with multimedia contents [11].

At the end of each presentation they expressed their opinion by means of a 5 values scale (VeryWeak, Weak, Neutral, Strong, VeryStrong[1]). As a consequence, the 8 scenes of the environment have been enriched (Fig. 2). Among these, two scenes contain more than one historical content, aiming at conveying information concerning the camp. As it can be seen from Fig.2, more than one video or photos with different level of emotional impact are enclosed to the scene 1 and 3. Two more scenes (scene 2 and 6) have been enriched with several virtual elements, also with different level of emotional impact, such as rain, darkness, fog, screams, flashing light etc. This kind of contents has been included in order to enhance the user experience in the course of the interaction with the environment. The remaining four scenes only include the 3D reconstruction of the camp, as it was in [11].

The new 3DVE release has been employed as Adaptive virtual environment. It allowed the virtual prisoner to dynamically adapt the visit to the user profile, choosing to avoid some media (historical content/virtual element) judged too upsetting for the

1 According to the definition of arousal dimension [14], a very weak emotional activation (as in the case of boredom) corresponds to a negative value of arousal. On the contrary, a strong emotional activation (for example engagement, just the reverse of boredom) corresponds to a positive value of the arousal. The neutral value corresponds to no emotional activation.

users sensibility or visiting only some zones of the entire virtual world, in order to maintain the current user's emotional state or to induce a desired one. In this way, users could be guided along well defined emotional and informative paths, and a more engaging overall experience could be possible.

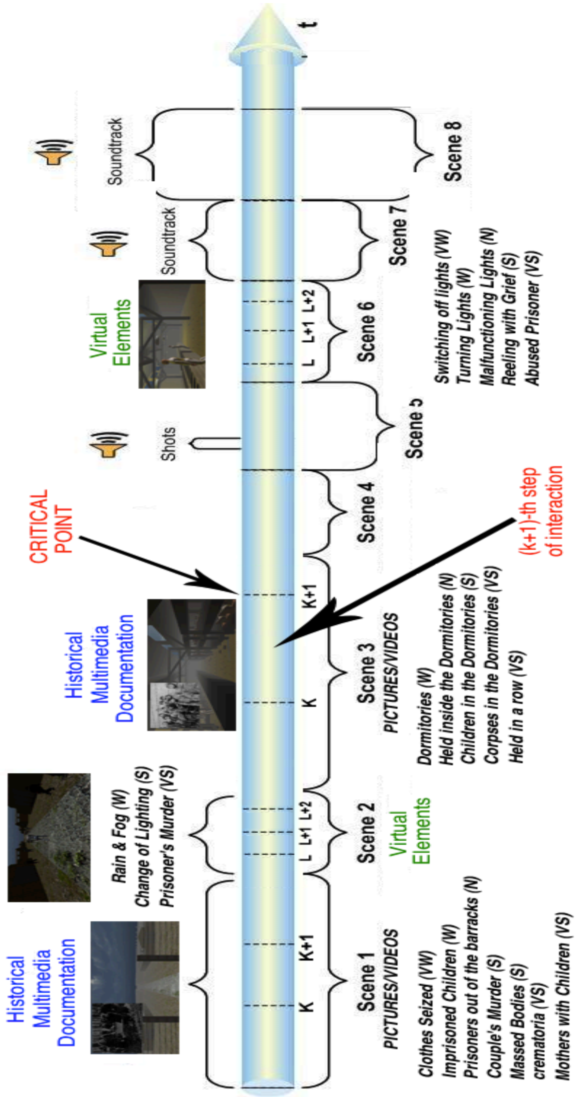


Fig. 2. Interaction Time-Line: Each Scene includes several examples of multimedia contents. Enclosed to each multimedia content an attribute indicates the level of impact of that content (VW: VeryWeak, W:Weak, N:Neutral, S:Strong, VS:VeryStrong). Dashed lines (K,K+1,.....L, L+1,...) on the interaction line are critical points (where the adaptation could take place). Scene 2 and 6 include critical points at fixed instant of time, during the interaction. In scene 1 and 3 critical points depend on the interaction.

3 Which Emotions and How to Measure Them

Which emotions more contribute to produce an immersive experience in the course of the interaction with the selected 3D environment? According to Picard, a right balance of positive and negative emotions should be induced in the user ("No Pain, No Gain" applications [15]). A first hypothesis is based on the levels of frustration and engagement. In the literature, "frustration" is defined as the psychological state due to a lacking or inhibited need because of external or endogenous reasons: The psychological state corresponding to the situation in which a subject is restrained or prevented to satisfy his own need or desire [16]. From this definition, it is plausible that a user feeling the psychological state of frustration in the course of the interaction with our 3DVE, could exhibit an empathic behavior with respect to the victims of the Shoah. This represents an essential requirement for a user to be "immersed" in the particular scenario we exploited in our study. However, a too "high" level of frustration could induce in the user the will to detach himself from the informational content (decreasing of the empathy). This could strongly affect the motivations to proceed with the 3DVE interaction. Moreover, "engagement" is defined as the state of heads-up and concentration to a stimulus or a task. It is considered as opposed to boredom, that is the state of temporary or enduring unsatisfaction due to inaction, idleness or repetitive and monotonous task [17]. Clearly, a user to be immersed should be engaged.

In order to measure these emotions and employ them in our adaptation mechanism, we started from the evidence that the interaction with an inherently emotional virtual environment (such as the Nazi's camp reconstruction) could be able to induce a huge amount of emotional variations, even in a short interaction. Moreover, it is well known the strong subjective nature of emotions: People feel emotions differently (with different intensity, for different reasons, by means of different mechanisms); even the same person, in different times, feels emotions differently due to the contest; lastly, the personality factors affect the attitude to feel emotions and to endure or not in an active emotional state. For these reasons, we decided to focus on the analysis of the user's frustration and engagement trend in well-defined interval of times, during the interaction with the environment (between two points where the environment adaptation is possible). This in order to avoid highly unstable results.

As a consequence, for each step of the interaction, the interaction could plausibly be considered as *satisfying* if *frustration is constant (not zero) and engagement is increasing*.

4 Emotional User Experience Recognition by Emotiv™ Epoc

Emotiv™ Epoc have developed a non-invasive, highly portable, bio-sensor headset to read the electrical activity in the brain to determine different cognitive and emotional states. It is a low-cost, easy to use neuroheadset developed for games. Based on the International 10-20 locations, it captures neural activity using 14 dry electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) plus CMS/DRL references, P3/P4 locations). The headset samples all channels at 128Hz, each sample being a 14 bit value corresponding to the voltage of a single electrode. Moreover, it provides a research SDK that enables to real-time display of the Emotiv™ Epoc headset data stream, including EEG, contact quality, FFT, gyro, wireless packet acquisition/loss display, marker events, headset battery level.

A heavy work on EEG signal processing is obviously out of the scope of this study. Directly based on the user's brain activity, Emotiv™ Epoc reads different emotion-related measures which are compatible with our intent: Among these (I) The *Instantaneous Excitement* (IE); (II) the *Long Term Excitement* (LTE); (III) the *Engagement*; (IV) and the *Frustration*. The first is experienced as an awareness or feeling of physiological arousal with a positive value. In general, the greater the increase in physiological arousal the greater the output score for the detection. The Instantaneous Excitement detection is tuned to provide output scores that more accurately reflect short-term changes in excitement over time periods as short as several seconds; LTE is experienced and defined in the same way as IE, but the detection is designed and tuned to be more accurate when measuring changes in excitement over longer time periods, typically measured in minutes. Engagement is experienced as alertness and the conscious direction of attention towards task-relevant stimuli[2]. Finally, frustration is experienced as the feeling of being upset or annoyed as a result of being unable to change or achieve something (http://www.emotiv.com). All these measures are detected to each variation[3].

5 The Adaptation Mechanism

Once implemented, the environment has been provided with a preliminary adaptation mechanism that, in each critical point (when the adaptation is possible, see Fig.2), on the ground of emotional information of the user (detected by the BCI), chooses the next multimedia content to be presented to the user. The adaptation mechanism implemented in our project is based on the reading and interpretation of values of frustration and engagement, as provided by the proprietary algorithms included in the affective suite of Emotiv Epoc. Particularly, we focus on a simple test for frustration and engagement trend, between two critical points. More formally: Be K the k-th critical point in the interaction (see Fig. 2), then:

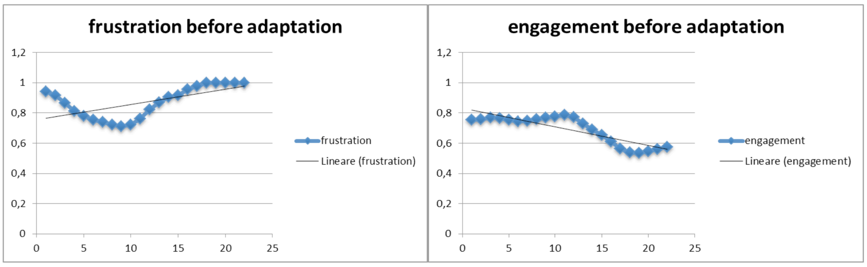
- The (k+1)-th step of the interaction is defined from the time interval between the critical points K and (K+1).
- CONT_i:*{$q_{i,m}$ | q is a multimedia content available in the i-th scene, with emotional impact m}* the set of all multimedia contents for the i-th scene.
- $\mathrm{TREND}_{(k+1)}(\mathrm{fru}, q_{i,m})$ (and $\mathrm{TREND}_{(k+1)}(\mathrm{eng}, q_{i,m})$) is the trend of the distribution of frustration (engagement respectively) values in the (k+1)-th step of the interaction, due to the presentation of content q_{im}, with emotional impact m.
- $\uparrow\mathrm{TREND}_{(k+1)}(\mathrm{fru}, q_{i,m})$ (and $\downarrow\mathrm{TREND}_{(k+1)}(\mathrm{fru}, q_{i,m})$) is the positive (negative respectively) Pearson correlation coefficient, with respect to detected values of frustrartion, during the (k+1)-th step of the interaction. In this case the frustration is increasing (decreasing respectively).

2 According to [http://www.emotiv.com] "Engagement" is only seen as an emotion. This differs from Nacke's works [7], in which "engagement is affeced from the ratio skills/challenge.

3 It is known that the Emotiv™Epoc headset data could be affected by facial muscle interference. Procedures to minimize this problems would involve the concurrent use of facial EMG and EOG monitoring to determine whether facial muscles and/or eye movements had any effect on the data. In our opinion, devices for EMG/EOG monitoring appears to be one more source of stress for a user interacting with the 3DVE. Accordingly, detected emotional data to be exploited in order to adapt the interaction would be affected too. As a consequence EMG/EOG devices seems to be unsuccessful according to our research's goals.

- $\uparrow TREND_{(k+1)}(eng, q_{i,m})$ (and $\downarrow TREND_{(k+1)}(eng, q_{i,m})$) is the positive (negative respectively) Pearson correlation coefficient, with respect to detected engagement's values, during the (k+1)-th step of the interaction. In this case the engagement is increasing (decreasing respectively).

In Fig. 3, an example of detection of the frustration and engagement (during the exploration of the BIIB latrines' virtual reproduction in scene 6) for a specific user are showed. A positive value of the Pearson coefficient corresponds to an increasing frustration (Fig. 3.a). Analogously, in Fig. 3.b, an example of decreasing engagement, for the same user, in the same step of interaction, is showed.



a) b)

Fig. 3. A real case: Scene 6, during the exploration of the BIIB latrines' virtual reproduction (see fig.2). Ordinate refers to detected frustration; Obscisse refers to the number of detections during the (L+1)-th step of interaction. a) detected increasing frustration; b) detected decreasing engagement.

As stated (see section 3), for each step of the interaction, the interaction is considered as *satisfying* if *frustration is constant (not zero) and engagement is increasing*.

The following adaptation mechanism originates:

IF $\uparrow TREND_{(k+1)}(fru, q_{i,m})$

THEN $SELECT(i, PRED(m)) = p_{i,PRED(m)},$

ELSE

IF $\downarrow TREND_{(k+1)}(fru, q_{i,m})$ **&** $(\downarrow TREND_{(k+1)}(eng, q_{i,m}))$

THEN $SELECT(i, SUCC(m)) = p_{i,SUCC(m)},$

ELSE $SELECT(i, m) = p_{i,m}$

Where:
- $q_{i,m}$ *and* $p_{i,m}$ *are in* $CONT_i$
- *m* is in the totally ordered set *IMP:{VeryWeak, Weak, Neuter, Strong, VeryStrong}*
- *PRED(m)*, *SUCC(m)* are the precedent and the subsequent values of *m, in IMP*
- *SELECT(scene, impact) operates in order to randomly select a multimedia content with impact "impact" that is available in the scene "scene".*

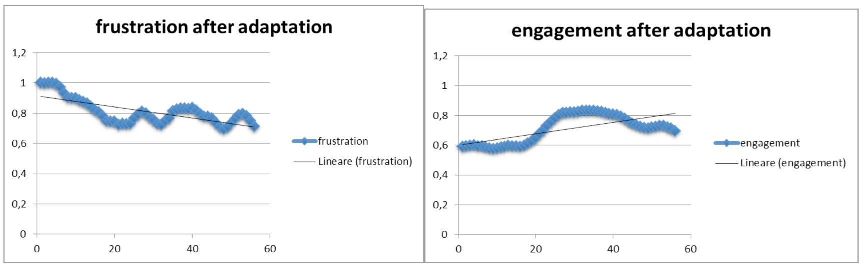
The condition $\uparrow TREND_{(k+1)}(fru, q_{i,m})$ checks if the user is too frustrated; in this case the interaction is not satisfying and the criterion tries to set the situation by showing a content with a weaker impact. The second condition check if the user is losing the focus; to avoid a further decreasing of the user's attention (and consequently a not immersive interaction) the criterion activates a content with stronger impact. The last condition corresponds to the case of a satisfying interaction; in this case the system proposes, in the next step, a content with the same emotional impact of the last one.

6 A Running Example

In this section a real detection and adaptation case is outlined: in the course of interaction the system shows the 6-th scene (a reproduction of the latrines in BIIB). Here, several virtual elements are included in the scene (see Fig. 2, scene 6). Moreover, 3 critical points are defined at fixed times during the interaction (Fig. 2, scene 6, critical point L, L+1, L+2). After few seconds starting from the beginning of the scene, a first multimedia content is activated at critical point L.

The engagement and the frustration detected at the (L+1)-th step of the interaction (with the corresponding linear regression lines related to the Pearson coefficient) are reported in Fig. 3: Frustration is increasing and engagement is decreasing. At this point, the adaptation mechanism will activate a content with a weaker impact than the last one, in order to produce a more satisfying and immersive interaction, in the (l+2)-th step of interaction. The system choses to "*turn off the light*" in order to hide details (a plausible source of frustration) about BIIB latrines virtual reproduction.

This solution proved to be the right one as the user's frustration consequently decreases and his engagement increases. Fig. 4 shows the frustration and engagement trends for the same user at the (L+2)-th step of interaction, when the system proposes a weaker content.



a) b)

Fig. 4. A real case: Scene 6, during the exploration of the BIIB latrines' virtual reproduction. a) detected decreasing frustration, after the adaptation of the interaction; b) detected increasing engagement, after the adaptation of the interaction.

7 Experiments and Results

Twelve users interacted with our environment in order to evaluate (I) *the quality of the adaptation in terms of the emotional impact of the selected contents* and (II) the user's *global satisfaction during the interaction, in terms of the dominant emotion, the immersion level of the environment and the level of interest in the contents*.

7.1 Experimental Protocol and Data Gathering

Twelve different subjects, with little knowledge about the selected domain interacted with the 3D environment. Their age ranges between 21 and 26 years. Fig. 5 shows the timeline of a session. Each experiment lasted 30 minutes on average[4].

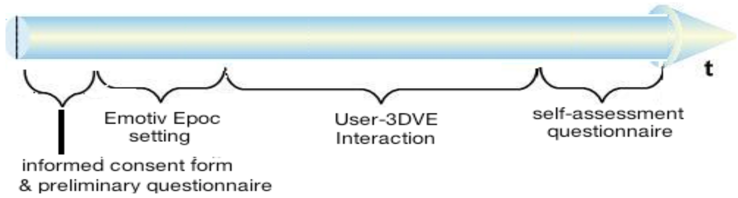


Fig. 5. Experimental Protocol

Each participant has been asked to sign an informed consent and, subsequently, to answer a preliminary questionnaire in order to set an initial profile of the user in terms of experience with 3D environment and interest in the domain of the experimentation. Each user has been left free to interact with the virtual environment.

In the course of the visualization of the 8 scenes, on the ground of the adaptation criterion (see section V) different contents have been showed to each user. At the end of the interaction each user answered a self-assessment questionnaire.

According to the self-assessment questionnaires, 70% of the users stated that the feeling of interest has been the dominant emotion in the course of the interaction. Moreover, 70% of the users declared that they were *sufficiently* interested in the contents of the environment, even if the interest has not declared to be the dominant emotion. Lastly, none of the user considered the environment not immersive and, in particular, 50% of them felt sufficiently immersed in the environment, while 30% wrote that they felt even rather immersed.

Furthermore, according to the adaptation mechanism, if in the k-th step of the interaction, the BCI detects an increasing frustration (a decreasing engagement respectively), the adaptation mechanism goal is to propose a content able to induce a decreasing (increasing respectively) of frustration (of engagement respectively) in the (k+1)-th step. As a consequence, a successful adaptation is achieved if frustration (engagement respectively) decrease (increase respectively) due to the content activated by the mechanism, at the k-th critical point. From the analysis of the gathered data, this successful situation occurred in the 56% of the cases, concerning both frustration and engagement.

In particular, in the successful cases, the adaptation better worked with respect to the increasing of frustration (74%). In all these cases, in the next step of the interaction, the environment showed a content that has been really able to induce a

4 The adaptation mechanism made impossible the a priori knowledge about the duration of each experiment. In this case the value represents the average duration on all the interactions.

decreasing of frustration. This result can be a consequence of the BCI ability to better detect negative emotions. One can't exclude that a more careful selection of the historical contents to be included in the environment (section II), in the design phase, could reduce this occurrence. This hypotheses is supported by the fact that, among all of the successful cases, 37% only can be attributed to the historical contents, while the remaining 63% is due to the virtual elements included to enrich the environment.

One more consideration concerns the number of adaptations performed: It can be inferred that, for all the users, the first scene requires the less number of adaptations. This can be due to the completely passive interaction with the environment: The plausible hypotheses to be tested is that this kind of interaction is not much satisfying, being responsible of a decrease of the engagement and an increase of frustration. If this is the case, it would be necessary to alternate between passive and active interaction with the environment.

Concerning the employed BCI, it should be noticed that in this paper we presented a preliminary work. More focus about the reliability of the BCI should be performed: e.g. how Emotiv™ Epoc defines and recognizes emotional concepts. Indeed, EEG signals provided by Emotiv™ Epoc have been shown to be reliable enough to detect well-known neuromechanisms, such as SSVEP. However, there is no scientific evidence about the emotional classifications made by Emotiv™ Epoc. Future further work will focus on testing the same methodology detailed in this paper on a more effective BCI (with respect to both hardware and software resources). In order to evaluate how our Adaptive 3D Virtual Environment positively impact (or not) users' interest and immersion two different groups of users will be tested (one with adaptation turned on, one without any adaptation of the virtual environment).

One last consideration: The dual aspect content/interaction is a key point in virtual reality. This work deal at the same time with the content (different historical materials) and the modalities of interaction (how the environment is "enriched"). In our opinion it's worth developing this aspect in the results, as it should lead to promising studies in the future.

References

1. I. Leite, A. Pereira., S. Mascarenhas, G. Castellano, C. Martinho, R. Prada, and A. Paiva "Closing the loop: from affect recognition to empathic interaction", in Proc. 3rd Int. Workshop Affective interaction in natural environments, New York, NY, 2010, pp. 43–48.

2. A. Choppin, "EEG-based human interface for disabled individuals: Emotion expression with neural networks". M.S. thesis, Tokyo Institute of Technology, 2000.

3. M. Murugappan, M. Rizon, R. Nagarajan, S. Yaacob, I. Zunaidi, and D. Hazry, "EEG feature extraction for classifying emotions using FCM and FKM," in Proc. 7th WSEAS Int. Conf. Applied Comp. and Applied Computational Science, Hangzhou, China, 2008, pp. 299-304.

4. D. O. Bos, "EEG-based Emotion Recognition: The Influence of Visual and Auditory Stimuli," 2007 [Online]. Available: http://hmi.ewi.utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf.

5. M. van Gerven, J. Farquhar, R. Schaefer, R. Vlek, J. Geuze, A. Nijholt, N. Ramsey, P. Haselager, L. Vuurpijl, S. Gielen, and P. Desain, "The brain–computer interface cycle," Journal of Neural Engineering, vol. 6, pp. 1-10, August 2009.

6. O. T. Zander., C. Kothe, S. Jatzev. and M. Gaertner, "Enhancing Human-Computer Interaction with Input from Active and Passive Brain-Computer Interfaces," in Brain-Computer Interfaces - Applying Our Minds to Human-Computer Interaction, London, U.K.: Springer, 2010, pp. 181-199.

7. M. Kivikangas, I. Ekman, G. Chanel, et al. Review on psychophysiological methods in game research. Proc. of 1st Nordic DiGRA, (2010)

8. C.L. Lisetti, and F. Nasoz, Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals. EURASIP J ADV SIG PR 2004, 11 (2004), 1672–1687.

9. G. G. Molina, T. Tsoneva, and A. Nijholt, “Emotional brain-computer interfaces,” in ACII 2009: Affective Computing & Intelligent Interaction, J. Cohn, A. Nijholt, and M. Pantic, Eds. Los Alamitos: IEEE Computer Society Press, Sep. 2009, pp. 138–146

10. G. Chanel, C. Rebetez, M. Bétrancourt, and T. Pun. Emotion assessment from physiological signals for adaptation of game difficulty. IEEE T Syst. Man Cy. A 41, 6 (2011), 1052–1063.

11. V. Carofiglio and F. Abbattista, “BCI-Based User-Centered Design for Emotionally-Driven User Experience,” in Cases on Usability Engineering: Design and Development of Digital Products, M. A. Garcia-Ruiz, Ed. Hershey, PA: IGI Global, 2013.

12. G. N. Yannakakis and J. Hallam, “Entertainment modeling through physiology in physical play,” Int. Jour. Human-Computer Studies, vol. 66, pp. 741–755, October 2008

13. E. Nacke, S. Stellmach, and C. A. Lindley, “Electroencephalographic Assessment of Player Experience: A Pilot Study in Affective Ludology,” Simulation & Gaming, vol. 42, pp. 632–655, February 2010.

14. J. A. Russell, “Core affect and the psychological construction of emotion”, Psychological Review, vol. 110, pp. 145-172, January 2003.

15. R. Picard, Affective Computing, Cambridge, MA: MIT Press, 1998.

16. J. Dollard, N.E. Miller, L.W. Doob, L.H. Moreover and R.R Sears, Frustration and aggression, New Haven, CT: Yale University Press, 1967.

17. R. Bartle, C. Bateman, N. Falstein, M. Hinn, and K. Isbister, Beyond Game Design: Nine steps Forward Creating Better Videogames, Charles River Media, 2009.