BrainArt: a BCI-based Assessment of User's Interests in a Museum Visit

Fabio Abbattista
Department of Computer Science,
University of Bari
Bari, Italy
fabio.abbattista@uniba.it

Valeria Carofiglio
Department of Computer Science,
University of Bari
Bari, Italy
valeria.carofiglio@uniba.it

Berardina De Carolis
Department of Computer Science,
University of Bari
Bari, Italy
berardina.decarolis@uniba.it

ABSTRACT

In the near future our brain will be connected to many applications. Recently research has concentrated on using the Brain Computer Interface (BCI) passively to recognize particular users' mental states. In this paper, we explore the possibility to harness electroencephalograph (EEG) signals captured by off-the-shelf EEG low-cost headsets to understand if an exhibition piece is of interest for a visitor. This information can be used to enrich the user profile and consequently to suggest artworks to see during the visit according to a recommendation strategy. The results of the exploratory study show the feasibility of the proposed approach

CCS CONCEPTS

• **Human-centered computing → User models**;

KEYWORDS

BCI, Engagement, Museum Visit

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1 INTRODUCTION

Human–computer interaction based on physiological signals is expected to be the next breakthrough in the field of multimedia systems, especially as far as affective computing is concerned. In this view, research presented in this study aims at developing a Brain-Computer Interface (BCI) to understand which exhibition piece the user is interested in during a virtual/real museum visit and use this information to personalize the visit using an appropriate recommendation strategy.

Usually electroencephalography (EEG) devices and BCI provide a way to measure brain activity and establish a direct communication between brain and computing systems. Useful applications of EEG have been developed mainly in the field of assistive technologies, helping disabled users to control external devices [9, 12]. However, with the advent of inexpensive and commercial EEG headsets, applications in new domains are being proposed (e.g., for enhancing the user experience during artistic performances [21], for monitoring attention levels during learning tasks [2], and so on). Taking into account that our brain processes constantly information and sensory inputs that pervade our daily life, it is easy to imagine applications that consider the impact of media (images, music, video, movies, etc.) upon the brain. In case of a museum visit, the number of items that users may look at is huge. In this case, personalized suggestions may be used to tailor the visit to users' interests and preferences. In recent years, the maturity of methods for the unobtrusive acquisition of implicit feedback [16] has grown to a level that allows its incorporation in personalized systems. To this aim, research has investigated the use of physiological signals to detect and recognize users' interest and engagement. Devices actually used to get this kind of feedback are mainly heartbeat monitors, galvanic skin response sensors and headsets to capture electroencephalogram (EEG) signals. In this paper we investigated on the use of a EEG low- cost commercial headset (MindWave - Neurosky) to capture and recognize the user interest in a artwork by detecting his engagement level during the visualization of a piece of art. The idea is to apply real-time brainwave signal detection techniques to get a feedback about which pieces of the exhibition are interesting for the user while he is looking at that item. To achieve our goal we developed a function to detect visual engagement and then, to test the feasibility of the approach, we performed a preliminary controlled experiment aimed at detecting interest of museum visitors in a item and relating it to the level of visual engagement.

Data collected in this experiment allowed learning a model for recognizing in real-time user's interest and use this information to enrich the user profile and provide recommendations accordingly.

The paper, after a brief section explaining the motivation for pursuing this approach, illustrates how visual engagement is calculated. Then the results of the study are presented. Conclusions and future work directions are discussed in the last section.

2 MOTIVATIONS AND BACKGROUND

Many authors have investigated the use of physiological signals to detect and recognize users' characteristics during the interaction [15]. Devices actually used to get bio and neuro-feedback have gained popularity especially in the context of videogames. Due to their ability to capture the engagement of a user beyond his conscious and controllable behaviors and in a transparent manner, EEG devices are being used in HCI context [18]. Since non-invasive commercial electroencephalography (EEG) devices have recently become more available on the market it is feasible to think about their use in domains such us music listening, video watching, etc.

EEG devices measure brain signals by placing electrodes on certain locations on the scalp that measure changes in electrical potential as neurons in the brain's cerebral cortex are fired [13].

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The collected signals are divided into five different frequency bands that have been proven to provide insight into a person's cognitive states such as attention/engagement and relaxation [17].

From the interaction viewpoint, BCI systems can be used in an active way, by allowing users to control a system by a conscious mental activity, and in a passive one, by monitoring the user brain activity to recognize mental states that are used as an input to the application [18] or to understand the user's mental state as a feedback to the received stimulus. In this case the interpretation of user's mental state could be used as a source of control to the automatic system adaptation [6].

This is the type of approach needed in our system, the indicators of "engaging" and "interest" as implicit feedback for personalizing the museum visit. Since in the last few years museums direct their efforts to provide personalized services both though their websites and on site offering personalized guide and descriptions of items, this information about the user can be used to build a user profile and then to provide recommendations [10]. An increasing number of museums use personalized museum guides to enhance visitors' experiences, attract new visitors, and satisfy the needs of a diverse audience [11, 19]. Ardissono et al. [4] provide a detailed survey of the field of personalized applications in cultural heritage. In our approach the BCI can monitor passively the user's experience during the museum visit in real time providing a feedback that can be used to personalize the visiting experience.

This approach has been used successfully in several projects. In the FOCUS system BCI is used to monitor engagement while children are reading [7]. Andujar and Gilbert [3] proposed a proof of concept investigating the ability to retain more information by incrementing physiological engagement using the Emotiv EPOC. Recently, Yan et al. [22] show how the measurement and analysis of audience engagement from EEG measurement level during a three-dimensional virtual theatre performance have positive impacts on the user experience. Abdelrahman et al. [1] report their experience in using EEGfeedback for detecting visual engagement of museum visitors using Emotiv EPOC.

Results of these research works are promising and, even if the experiments were performed on a small number of users, they show the potentiality of the approach. Therefore we decided to investigate if the same type of information about user's mental state could be captured using a cheaper headset with only one dry electrode.

3 THE PROPOSED APPROACH

The visitor experience in a museum is mainly shaped by his behavior based on his interest and engagement in the exhibited items. The cognitive component of interest corresponds to the activation of the pre-frontal cortex of the brain captured using EEG signals. We propose a museum experience that utilizes brain signals acquired by commercially available BCI systems to sense the museum visitors' engagement in exhibits and provide real- time feedback to the visitor with personalized recommendations.

The recent availability of low-cost commercial and comfortable EEG headsets makes the use of this technology affordable for a museum that can then serve a large number of users. In this work, Neurosky [8] wireless EEG Mindwave device is used (Figure 1).

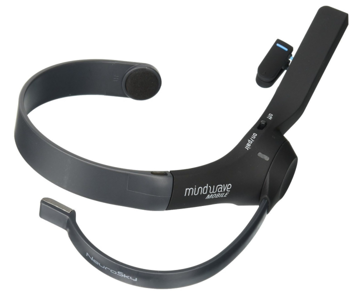

Figure 1: Neurosky wireless EEG Mindwave device.

The headset is equipped with a single-channel EEG sensor and an electrode that rests on the forehead on the FP1 position according to the international 10-20 system and a second electrode that touches the ear. This sensor is used as ground to filter out the electrical noise. Sensors are capable of detecting raw EEG signals, frequency of different brainwaves: Delta (0-3 Hz), Theta (4-7 Hz), Alpha (8-12 Hz), Beta (12-30 Hz) and Gamma (30-100 Hz), and two mental states (attention and meditation) that are calculated by proprietary algorithms. Neurosky MindWave was chosen due to its affordability, portability, wireless connection capability and the availability of an open source API (Application Programming Interface). Finally, it offers unencrypted EEG signal.

We are aware that a major limitation in using this headset is the accuracy of the EEG signal, because this headset has only one electrode. However, our challenge is to have as much information as possible, avoiding stressing the user in terms of the discomfort of the device. The size and comfort of the device used may allow for a real-time assessment of users preferences and then for a provision of fine-tuned suggestions and content during the visit.

3.1 Visual Engagement Measurement

Electroencephalography (EEG) is a method to measure the brain's electrical activity. Usually the EEG signals can be affected by noise due to eye movements, muscle noise, heart signals, and so on. The BCI allows filtering the noise signal while preserving the essential EEG signals. EEG frequencies have been extensively studied and can provide insight into user mood and emotions such as excitement, meditation, pleasure and frustration. EEG measures are also sensitive to cognitive states including engagement and attention.

As far as engagement measurement is concerned, Pope et al. [14] defined the following formula relying on three of the frequency bands which correlate EEG signals with task engagement: $Engagement = \beta/(\alpha + \theta)$.

The formula uses the Alpha (α) band (7-13 Hz) associated with relaxation, the Beta (β) band (13-30 Hz) associated with attentiveness and focus, and finally the Theta (θ) band (4-7 Hz) associated with dreaminess and creativity.

Berka et al. [5] has shown that the engagement index reflected a person's process of visual scanning and attention. This formula has been used successfully in several projects with encouraging results [1, 3, 17].

4 AN EXPLORATORY STUDY

In the following sections, we discuss our experimental setup, data collection and analysis and, at the end, our findings.

4.1 Participants and Methodology

Twenty-four participants took part in the study aged from 16 to 60 (mean age of 26.9 with a standard deviation of 10.75). Sixteen of them were male and eight were female. Twenty participants were students and four were part of the teaching staff.

According to the purpose of this study we selected 20 artworks from *wikiart.org*. The selection was made according to the five main styles present in wikiart classification: **Medieval Art**, **Renaissance Art**, **Post Renaissance Art**, **Modern Art**, **Contemporary Art**. For each style, we selected artworks of two different genres: painting and sculpture.

Before starting the experiment, participants were given an overview regarding the EEG technology, experiment, and the type of data collected. Consent was signed by all of the subjects. Participants were trained on how to use the headset and the application. Before the experiment they were asked to wait few minutes to stabilize EEG signals. The total time of the experiment was approximately 5 minutes for most of the participants. After completing the experiment, participants were asked to answer a questionnaire about their demographics, health status and other questions to rate the device's comfort level. The questionnaires showed that all of the subjects did not suffer from any health issues prior to the experiments. The experiment was conducted in a room with controlled lighting in a research lab in our Department. Both the experimental tasks and the EEG recording were controlled with the same computer.

4.2 Data Acquisition

In order to acquire data to learn a model that can be used to recognize the user's interest, we implemented an interface to randomly show the selected artworks to the user.

The adopted protocol is the following (Figure 2). At the beginning of the interaction the user is asked to relax for 10 seconds. The data recorded in this time represents the baseline for that user. At the end of this relaxation period, the artwork image, selected randomly, is shown to the user for 10 seconds. During this time, the brain signals are recorded and immediately after an evaluation screen is shown to the user. Through this screen, the user expresses his judgment in terms of "I'm interested" (I), "I'm not interested" (NI) or "Neutral" (N). In order to relax the mind and move on to the next artwork, a neutral screen is shown again for 10 seconds.

Band power data is used to calculate visual engagement. In particular, we use Pope's formula to calculate a vector of engagement values both for the initial relax time (*EngRelax*) and for each artwork visualization time (*EngImage*). Starting from these data we calculate the Euclidean distance between the so acquired two vectors. This distance represents the **Visual Engagement Index (VEI)** and it is stored in a log file together with the evaluation explicitly expressed by the user. A total of 580 instances were collected.

4.3 Implicit Feedback Recognition

To implement a process able to use EEG signals as implicit feedback, we used the data collected during the experiment to learn a classification model. To this aim we used the WEKA platform [20]. According to research on the topic we applied the SVM algorithm and, in particular, we used the SMO (Sequential Minimal Optimization) algorithm that handles multiclass data by combining binary SMOs. The three classes of interest were NI= Not Interesting, N=Neutral, and I=Interesting.

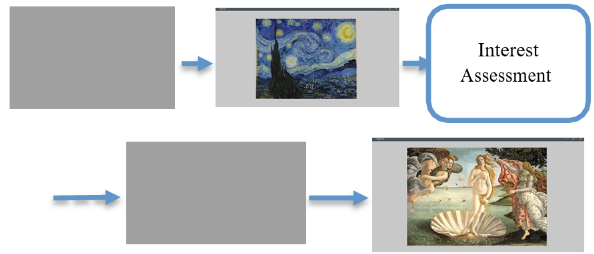

Figure 2: An example of interaction sequence during the experiment.

Results, calculated using 10-fold cross-validation, show an average accuracy on three classes of 0.75 and a average F1-measure of 0.672. Analyzing the classification results in more details by looking at the confusion matrix (see Table 1), we noticed that the majority of instances of class N, corresponding to a neutral interest, were misclassified. This result is encouraging and, even if it does not provide a way in detecting nuances in the level of interest of the user, it is able to discriminate between interesting and not interesting items.

Table 1: Confusion Matrix

NI	N	I	
198	95	4	**NI**
95	9	36	**N**
10	0	228	**I**

Supported by this result we studied the feasibility of using such in real-time by predicting user's interest while looking at an exhibition piece. To this aim we conducted a very simple experiment. We selected 20 new items from wikiart.org equally distributed along the 5 styles used for the first experiment.

We asked to 10 participants, aged between 19 and 52 y.o, (avg=25.3, std.dev=9.3) to perform a task similar to the one of the first experiment. Each participant had to wear the headset and look at 2 randomly selected artworks according to the protocol described previously. This time, the interest or not towards the artwork was indicated by the system according to the result of the classification of the VEI done using the learned model. Each participant could agree or not with the system by changing the predicted interest. *Hit Ratio* is a way of calculating how many "hits" a user has in a list of recommended items. A "hit" could be defined as something that the user has clicked on, purchased, or saved/favourite (depending on the context). In this case we consider a "hit" the agreement between the system prediction and the explicit user evaluation. If we consider this as a measure of success of the classifier then the proposed approach showed to be effective since in 70% of cases the user agreed with the system prediction.

5 CONCLUSION AND FUTURE WORK DIRECTIONS

Detecting visitor's interest and emotions implicitly from EEG signals using low-cost and commercially available devices is the main aim of our research. In particular we plan to employ this approach in the context of personalized virtual or real museum visit. In this paper, we have presented how the EEG signals, gathered using the Neurosky MindWave device, can be used as a potential source for implicit feedback recognition. To achieve our goal we developed a function to detect visual engagement from EEG signals and then, to test the feasibility of our approach we performed a preliminary controlled experiment aimed at predicting in real-time user's interest in a piece of art. Results show the feasibility of the proposed approach since, using SVM, we had a good accuracy on three classes (not interesting, neutral and interesting). The implicitly recognized interest can then be used to enrich the user profile and personalize museum visits.

While the work presented here is focused on understanding how to relate observations to predicted ratings, we then hope to develop and implement a prototype that will give us some insight into how implicit feedback can be used effectively in an application environment. For instance the level of engagement can be used not only to suggest what to see during the visit, but also to adapt the description content of a piece of art.

We also plan to conduct experiments using a more accurate commercial device with a major number of electrodes in order to detect not only the interest aroused while looking at an artwork but also to recognize the elicited emotion.

REFERENCES

[1] Yomna Abdelrahman, Mariam Hassib, Maria Guinea Marquez, Markus Funk, and Albrecht Schmidt. 2015. Implicit Engagement Detection for Interactive Museums Using Brain-Computer Interfaces. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. ACM, New York, NY, USA, 838–845. https://doi.org/10.1145/2786567.2793709

[2] Ray Adams, Richard Comley, and Mahbobeh Ghoreyshi. 2009. The Potential of the BCI for Accessible and Smart e-Learning. In *Universal Access in Human-Computer Interaction. Intelligent and Ubiquitous Interaction Environments*, Constantine Stephanidis (Ed.). Springer Berlin Heidelberg, Berlin, Heidelberg, 467–476. https://doi.org/10.1007/978-3-642-02710-9_51

[3] Marvin Andujar and Juan E. Gilbert. 2013. Let's Learn!: Enhancing User's Engagement Levels Through Passive Brain-computer Interfaces. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, New York, NY, USA, 703–708. https://doi.org/10.1145/2468356.2468480

[4] Liliana Ardissono, Tsvi Kuflik, and Daniela Petrelli. 2012. Personalization in Cultural Heritage: The Road Travelled and the One Ahead. *User Modeling and User-Adapted Interaction* 22, 1-2 (April 2012), 73–99. https://doi.org/10.1007/s11257-011-9104-x

[5] Chris Berka, Daniel J Levendowski, Michelle N Lumicao, Alan Yau, Gene Davis, Vladimir T Zivkovic, Richard E Olmstead, Patrice D Tremoulet, and Patrick L Craven. 2007. EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, space, and environmental medicine* 78, 5 (2007), B231–B244.

[6] Laurent George and Anatole Lécuyer. 2014. *Passive Brain–Computer Interfaces*. Springer London, London, 297–308. https://doi.org/10.1007/978-1-4471-6584-2_13

[7] Jin Huang, Chun Yu, Yuntao Wang, Yuhang Zhao, Siqi Liu, Chou Mo, Jie Liu, Lie Zhang, and Yuanchun Shi. 2014. FOCUS: Enhancing Children's Engagement in Reading by Using Contextual BCI Training Sessions. In *Proceedings of the 32Nd Annual ACM Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 1905–1908. https://doi.org/10.1145/2556288.2557339

[8] NeuroSky Inc. 2010. Brain Wave Signal (EEG) of NeuroSky, Inc. http://www.frontiernerds.com/files/neurosky-vs-medical-eeg.pdf. (15 Dec 2010).

[9] Ivo Käthner, Jean Daly, Sebastian Halder, J Räderscheidt, Elaine Armstrong, Stefan Dauwalder, Christoph Hintermüller, Arnau Espinosa, Eloisa Vargiu, Andreas Pinegger, et al. 2014. A P300 BCI for e-inclusion, cognitive rehabilitation and smart home control. In *Proceedings of the 6th International BCI Conference Graz 2014*.

[10] Tsvi Kuflik, Oliviero Stock, Massimo Zancanaro, Ariel Gorfinkel, Sadek Jbara, Shahar Kats, Julia Sheidin, and Nadav Kashtan. 2011. A Visitor's Guide in an Active Museum: Presentations, Communications, and Reflection. *J. Comput. Cult. Herit.* 3, 3, Article 11 (Feb. 2011), 25 pages. https://doi.org/10.1145/1921614.1921618

[11] Ioanna Lykourentzou, Xavier Claude, Yannick Naudet, Eric Tobias, Angeliki Antoniou, George Lepouras, and Costas Vassilakis. 2013. Improving museum visitors' Quality of Experience through intelligent recommendations: A visiting style-based approach.. In *Intelligent Environments (Workshops)*. 507–518.

[12] José del R. Millán, Rüdiger Rupp, Gernot Mueller-Putz, Roderick Murray-Smith, Claudio Giugliemma, Michael Tangermann, Carmen Vidaurre, Febo Cincotti, Andrea Kubler, Robert Leeb, Christa Neuper, Klaus Mueller, and Donatella Mattia. 2010. Combining Brain–Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges. *Frontiers in Neuroscience* 4 (2010), 161. https://doi.org/10.3389/fnins.2010.00161

[13] Ernst Niedermeyer and FH Lopes da Silva. 2005. *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins.

[14] Alan T Pope, Edward H Bogart, and Debbie S Bartolome. 1995. Biocybernetic system evaluates indices of operator engagement in automated task. *Biological psychology* 40, 1-2 (1995), 187–195. https://doi.org/10.1016/0301-0511(95)05116-3

[15] George E. Raptis, Christina Katsini, Marios Belk, Christos Fidas, George Samaras, and Nikolaos Avouris. 2017. Using Eye Gaze Data and Visual Activities to Infer Human Cognitive Styles: Method and Feasibility Studies. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization (UMAP '17)*. ACM, New York, NY, USA, 164–173. https://doi.org/10.1145/3079628.3079690

[16] Björn W. Schuller. 2016. *Acquisition of Affect*. Springer International Publishing, Cham, 57–80. https://doi.org/10.1007/978-3-319-31413-6_4

[17] Daniel Szafir and Bilge Mutlu. 2012. Pay Attention!: Designing Adaptive Agents That Monitor and Improve User Engagement. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. ACM, New York, NY, USA, 11–20. https://doi.org/10.1145/2207676.2207679

[18] Desney S. Tan and Anton Nijholt. 2012. *Brain-Computer Interfaces: Applying Our Minds to Human-Computer Interaction*. Springer Publishing Company, Incorporated.

[19] Ed S. Tan and Katri Oinonen. 2009. Personalising Content Presentation in Museum Exhibitions - A Case Study. In *Proceedings of the 2009 15th International Conference on Virtual Systems and Multimedia (VSMM '09)*. IEEE Computer Society, Washington, DC, USA, 232–238. https://doi.org/10.1109/VSMM.2009.42

[20] Ian H Witten, Eibe Frank, Mark A Hall, and Christopher J Pal. 2016. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.

[21] Shuo Yan, GangYi Ding, Hongsong Li, Ningxiao Sun, Yufeng Wu, Zheng Guan, Longfei Zhang, and Tianyu Huang. 2016. Enhancing Audience Engagement in Performing Arts Through an Adaptive Virtual Environment with a Brain-Computer Interface. In *Proceedings of the 21st International Conference on Intelligent User Interfaces (IUI '16)*. ACM, New York, NY, USA, 306–316. https://doi.org/10.1145/2856767.2856768

[22] Shuo Yan, GangYi Ding, Hongsong Li, Ningxiao Sun, Yufeng Wu, Zheng Guan, Longfei Zhang, and Tianyu Huang. 2016. Enhancing Audience Engagement in Performing Arts Through an Adaptive Virtual Environment with a Brain-Computer Interface. In *Proceedings of the 21st International Conference on Intelligent User Interfaces (IUI '16)*. ACM, New York, NY, USA, 306–316. https://doi.org/10.1145/2856767.2856768