Implicit Engagement Detection for Interactive Museums Using Brain-Computer Interfaces

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Abstract
A rich museum experience is one that is engaging, educating and enjoyable to the visitors, such experiences can only be achieved by personalizing and enriching the museum experience according to the visitor's state. Neural signals from the brain can provide information about the affective and cognitive state of the person implicitly. With the rise of commercial Brain-Computer Interface devices, this technology can be utilized in extracting information to adapt various experiences to the state of the person. We propose a concept and preliminary study which uses brain signals from commercial grade Brain-Computer Interface (BCI) devices to implicitly detect museum visitors' engagement in the exhibited objects. Our concept and output of the study envision an experience where real time feedback based on visitors engagement is provided and the whole museum experience is tailored to each visitor's taste. In future work, we aim to gain external validity by testing our prototype in a museum setting.

Author Keywords
EEG; BCI; Museum Guide;User Defined Exhibitions;Interaction in Museums;Interest classification; Wearable Computing.

ACM Classification Keywords
H.5.2 [Information Interfaces and Presentation]: User Interfaces.Graphical User Interfaces.

Introduction

Museums exhibit large number of objects, one of the main challenges is to design and set the order of which the objects are organized especially in large museums of multiple rooms. Usually curators organize exhibits either by date, storyline, theme, etc.. However, the setting might not fit all visitors due to the diversity of interest and preferences. HCI Researchers tackled this by introducing an explicit interactive personalized dimension to the experience [3, 15]. On the other hand, this type of interaction could also have negative impacts [8, 9].

One sensing modality that can be used to implicitly capture the interest of museum visitors would be using physiological signals, particularly neural signals. Using the brain as a way to implicitly understand human emotions can be used in building personalized and interactive experiences. A Brain-Computer Interface (BCI) is able to capture signals from the brain elicited by neurons that are fired when an area of the brain is active. BCIs have been recently available as commercial and portable devices and have been used in the non-medical field with non-disabled users. Commercial BCIs have succeeded as passive BCI systems which use the neural signals in a biofeedback loop to gain insight about the cognitive and emotional state of users and adapt systems accordingly. For example, in personalizing computer games by adapting the content and difficulty depending on the player's state of mind [22], or in helping people and children sustain their focus and hence retain more information while learning [2, 10] based on brain signal measurements of engagement.

In this paper we present the results of a preliminary controlled lab study which aims to detect visual engagement of museum visitors using commercial BCI. We develop a user independent visual engagement index which correlates with subjective measures of engagement provided by users. We also discuss our concept and the next steps of our work towards building personalized museum tours based on implicit visual engagement detection.

Related Work

In the following, we discuss prior work in two different areas (1) tools and techniques aimed to enhance and personalize the museum visit, and (2) the usage of commercial BCI to extract and detect users engagement.

Interactive Museum Experience

Human computer interaction researchers and curators are examining ways to enrich and enhance the experience of museums and exhibits. By deploying various tools and technologies, an interactive dimension has been added to objects in museums. Grammenos et al. [7] explored having a touch enabled surface, where a digital catalog is presented to the visitors and they can browse through it for the objects in the exhibition. They also developed a wall sized display, where visitors can view additional content using a physical magnifying glass. Additionally [6] proposed the system *PaperView* where regular paper sheets are placed and additional information based on the context is projected on the paper sheet. Schneegass et al. [17] introduced the concept of *Point. Explore. Learn.* aiming to use more natural interaction techniques to provide an exploratory interaction with exhibited objects. Moreover they developed the *interactive torch*, where an interactive device in the form of a torch is used by visitors to explore additional information. Further work included a post museum visit interactive dimension. The addition of RFID tags to enable visitors to tag and interact with exhibits in a museum [9, 12] adding a post visit personalization experience, where the visitor can revisit the objects later on a personalized website.

Hornecker [8] investigated the use of multi-touch table for interaction in museums and further explored the gain of knowledge using an interactive installation. However, further studies reported the lack of self-explanatory technology augmentation and that technologies are not fully understood by visitors [9]. In this work we aim to exploit more intuitive and implicit interaction on which we rely on the brain signals as bases of engagement detection to introduce interactive exhibitions.

Using Brain Signals to Detect Engagement

Brain signals provide a lot of information about the cognitive and emotional state of humans. There are many ways to measure brain signals using invasive and non-invasive techniques. Non-invasive techniques which are more suitable for HCI applications such as functional near infra-red spectroscopy (fNIRS) and electroencephalography (EEG) have recently become more available to the masses and affordable with the emergence of commercial devices (e.g. Neurosky [1], Emotiv [2]).

EEG devices measure brain signals by placing electrodes on certain locations on the scalp which measure changes in electrical potential as neurons in the brain's cerebral cortex are fired [20]. The collected signals fall into five different frequency bands which have been extensively studied and are proven to provide insight into a person's cognitive states such as attention/engagement and relaxation [19].

In 1995, Pope et. al defined the following formula relying on three of the frequency bands which correlate EEG signals with task engagement[14]:

$$E = \frac{\beta}{\alpha + \theta}$$

[1]Neurosky: http://www.neurosky.com/
[2]Emotiv: http://www.emotiv.com/

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.Szafir et.al utilized the engagement formula and the high temporal resolution of EEG for detecting engagement in real-time and correlating it to external stimuli. The work uses the Neurosky Mindset commercial BCI to design adaptive agents that monitor the attention levels of students and detecting attention drops. Behavioral techniques were employed by robotics agents to regain students' attention [19]. Similarily, Huang et. al also used the engagement formula and designed the *FOCUS* system in which the Emotiv EPOC was used to monitor a child's reading engagement and provide BCI training tasks contextually to attempt to elevate attention and engagement levels [10]. Andujar and Gilbert proposed a proof of concept investigating the ability to retain more information by incrementing physiological engagement using the Emotiv EPOC [2]. They proposed measuring engagement in three different ways: using Emotiv proprietry algorithms, using subjective measures (surveys) and using the engagement formula [2].

Other researchers investigated the efficiency of the Emotiv EPOC commercial EEG device in detecting states of attention and relaxation [5, 18]. The proprietary values provided by the EPOC for engagement, short-term and long-term excitement were used in an intelligent tutoring system (ITS) student model during different scenarios prompting high and low cognitive loads [5]. Previous work using the EPOC to successfully detect states of attention using a reduced number of electrodes was done by Yaomanee et. al in[21].

Concept

In our work we assess the feasibility of using neural data in creating personalized and interactive museum experiences based on the visitors' preferences. Prior research defined a full cultural heritage experience, be it a museum or an art gallery, as one in which visitors experience entertainment, immersion, education and pleasure [4, 13]. As human physiology can provide a lot of implicit cues about person's state, physiological computing systems can monitor the museum experience in real time where the cognitive and emotional state of the museum visitor is passively sensed in real-time forming a bio-feedback loop where the experience is personalized in various ways in a process of 'adaptive curation'.

The visitor experience in a museum is mainly shaped by his/her behavior based on his/her interest and engagement in the exhibited items. The conceptual model for interest states that a visitor's interest is affected by emotional and cognitive aspects. Karrain et. al operationalized the interest model and defined the cognitive component of interest as the activation of the pre-frontal cortex of the brain captured using EEG signals.

We propose a museum experience which utilizes brain signals acquired by commercially available BCI systems to sense the museum visitors' engagement in exhibits and provides real-time feedback to the visitor with suggestions to personalize their experience. EEG signals being highly user dependent, require prior training to truly be able to detect engagement of each visitor. Our concept, depicted in Figure 1, suggests that museum visitors entering a museum would first be presented a selection of photographs showing various exhibited items covering a range of topics from this museum. The EEG signals collected would then be used to calibrate and train the engagement detection model for this particular visitor. The visitor will then start his/her museum tour, upon standing at each exhibit the EEG signals will be labeled, filtered using popular EEG signal pro-

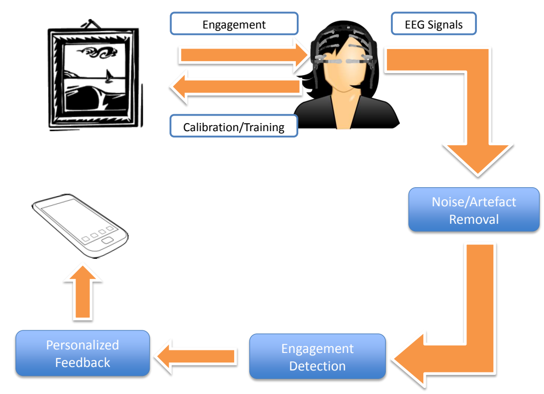

Figure 1: Concept of Implicit Engagement Detection in Museums

cessing algorithms, and the engagement index for the exhibit will be computed in real time. The visitor will then receive cues on his/her mobile phone recommending other exhibited items that match the engagement levels detected previously to personalize his/her experience. At the end of the visitors' tour they will be provided with a summary of their engagement throughout the whole museum visit making museum experiences rich, enjoyable and personal.

Data Acquisition & BCI Engagement Detection

Pilot Study

In order to assess the feasibility of our concept and answer the question "Can commercial grade BCI be able to detect engagement in museum settings?" we conducted a first pilot study in a controlled setting. We recruited 10 participants(with an average age of 25.1 years, SD=2.77) using university mailing lists. All participants were students in different majors.

We chose the EEG-based commercial BCI system Emotiv EPOC BCI which has 14 electrodes from electrode locations based on the 10-20 international electrode positioning system and provides access to the raw data. The EPOC provides wireless connectivity to connect to the PC, which makes it portable and suitable to providing a better user experience than other more complex BCI devices. Several research studies, such the ones done by Yaomanee et al. [21], and Huang et al. [10], prove that the electrodes placed on the frontal and occipital lobe perform a good approach to obtain cognitive and visual information from the EEG data. According to this, electrodes AF3, AF4 (frontal) and 01, 02 (occipital) were selected for our study.

Ten different pictures covering ten different topics that can be found in museums (History, Travel, Birds, Animals, Plants, Egyptology, Technology, Architecture, Automotive, Roman) were chosen. We simulated viewing objects in a museum through displaying pictures of these topics on a 30” screen, with an informative title on each picture. Participants were seated approximately 1m away from the screen as shown in figure 2. All participants were not familiar with the shown pictures and the displaying order of the pictures was randomized. The setup took between 10-15 minutes and the complete study took approximately 30 minutes per participant.

We used a repeated measures design with two levels of feedback for engagement in the shown topic: implicitly using the EPOC and explicitly by asking users about their interest level in the displayed image using a 7-point likert scale. Participants were seated in a controlled environment and fitted with the EPOC 2. To have a baseline for comparison of EEG signals, we first recorded 60 seconds of

Figure 2: Participant viewing pictures in stationary setup

Figure 3: Pictures viewing process

relaxation EEG at the beginning of each session where participants were instructed to relax by closing their eyes. Each picture was then shown for 20 seconds, followed by 10 seconds in which the participants were asked to rate their engagement subjectively, and finally a relaxation phase of 20 seconds by showing a black screen. The process is depicted in figure 3.

The Emotiv includes a frequency pass-band filter from 0,2 to 45 Hz as well as two digital notch filters at 50 and 60 Hz in order to avoid interferences from electrical devices. However, further noise and artefact removal was necessary. A Finite Impulse Response (FIR) high-pass filter was used for rejecting the frequency components lower than 1 Hz. EOG artifacts, generated from eye movements/blinking, were automatically removed using the Second Order Blind Inference (SOBI) algorithm which previously showed high performance among the existing algorithms for removing eye movement and blink artifacts from EEG data [11]. After the noise and artefact removal, the power spectrum of Alpha, Beta and Theta frequency bands were extracted to be able to calculate the engagement as per formula 1.

Visual Engagement Detector Score
Following artefact removal from the EEG *baseline* and *pictures* segments, the Engagement Index (EI) for each segment was calculated via formula 1. According to the circumplex model of affect [16], engagement and interest are associated with positive valence and arousal. There have been many studies correlating hemispheric asymmetry with emotions [1, 23]. Hence, we calculated the assymetric engagement (AE) where the difference between the right hemisphere electrodes (AF4, O2) engagement indices and the left hemisphere electrodes (AF3, O1) was used.

$AE_{Occipital}$=EI_{O2}-EI_{O1}
$AE_{Frontal}$=EI_{AF4}-EI_{AF3}

Next we aimed to weigh the visual information extracted from occipital lobe electrodes against the frontal lobe electrodes. We used the following equation to calculate the engagement score (ES):

$$ES_{pic,relax} = a \cdot AE_{Occipital} + b \cdot AE_{Frontal} \ (b = 1 - a)$$

It was concluded that the best result were obtained when $a = 0.85$ and thus, b$= 1 - a =$0.15. This results that 85% of the visual interest comes from visual information, whereas the thinking initiation represent the other 15%. This relationship is supported by other research studies, based in EEG data extracted from the occipital lobe (O1 and O2 electrodes) to create a cognitive system [19]. The

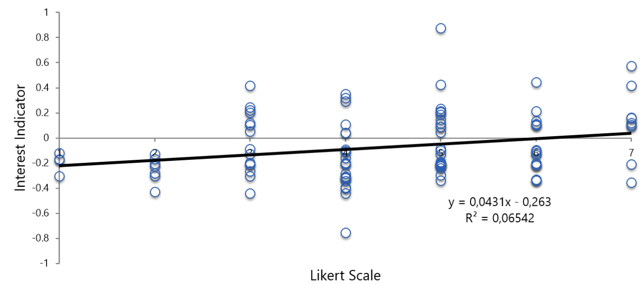

Figure 4: Linear Correlation between the Likert Scale of all the Participants and the Visual Engagement Score

Euclidean distance between ES_{pic} and the baseline relaxation ES_{relax} was the calculated. Finally, we defined the *Visual Engagement Detector Score* (VEDS) as follows:

$$VEDS = \begin{cases} If\ ES_{pic} > ES_{relax},\ +Distance \\ If\ ES_{pic} < ES_{relax},\ -Distance \end{cases}$$

Results
Pearson product-moment correlation was used to compute the correlation between Likert scale data with the computed *Visual Engagement Detector Score* per user $(r(98) = 0.256, p < 0.01)$. Figure 4 depicts the linear correlation between the Likert scale scores and the engagement scores of all participants (user independent). This found correlation, although low, shows promising results in using BCI to detect visual engagement.

Conclusion and Future Work
Since this is preliminary work in progress, we plan to explore the limitations in more depth. As a following step we need to validate our *VEDS* scoring system with a larger number of subjects and with a wider variety of images. We would also repeat the experiment on different days to

ensure internal validity as the emotional state of a person would change on different days and their EEG signals may be different due to external conditions. A further step would be evaluating the engagement detection algorithm in real time and more realistic settings. We aim to increase the external validity of system by conducting a second study in which participants walk in a real environment simulating a museum setting. This will introduce motion artefacts and more challenges, which we aim to address. Furthermore, we plan to consider the challenges of deploying a BCI in a museum environment regarding curators and visitors. The final vision of our project would be to realize the concept (figure 1) where a mobile application will be implemented in which the real time feedback will be provided to the museum visitor.

Detecting visitor engagement implicitly using brain signals with commercially available devices will pave the road towards creating richer museum experiences in the future. High engagement levels can for example trigger more interaction in the form of projecting more content on certain exhibits. Personalized guided tours suggesting similar exhibits depending on engagement levels. Finally, implicit engagement detection from large numbers of museum visitors can help museum curators organizing and adapting the museum to suit their visitors' tastes.

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