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Detecting boredom from eye gaze and EEG

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ABSTRACT

The recent proliferation of affordable physiological sensors has boosted research and development efforts of emotion-aware systems. Boredom has received relatively little attention as a target emotion, and we identified a lack of research on the relationship between eye gaze and electroencephalogram (EEG) when people feel bored. To investigate this matter, we first conducted a background study on boredom and its detection by physiological methods. Then, we designed and executed an experiment that uses a video stimulus – specifically designed for this experiment, yet general enough for other boredom research – with an eye tracker and EEG sensor to elicit and detect boredom. Moreover, a questionnaire was used to confirm the existence of boredom. The experiment was based on a hypothesis that participants may feel bored when their gaze deviates from an expected area of interest, thus indicating loss of attention. The results of the experiment indicated correlations between eye gaze data and EEG data with all participants ($N = 13$) when they felt bored. This study can be useful for researchers who have interest in developing boredom-aware systems.

1. Introduction

Emotion-aware computer systems began to gain interest since researchers realized that one-size-fits-all experiences are not sufficient to satisfy the needs of heterogeneous users. In the domain of education, Picard [1] used a piano-teaching computer system to demonstrate the advantages of personalized learning by proposing that the computer could provide appropriate guidance to the learner by observing their emotions. In another example, Chanel et al. [2] applied emotion-awareness to a game so as to maintain the player's engagement. Their goal was to detect the player's emotional state using a categorization scheme comprising three classes: boredom, anxiety and engagement. In order to maintain the player's engagement, they proposed to change the difficulty of the game when the player's emotional state is detected to be boredom or anxiety.

The aforementioned examples illustrate some of the potential affordances that emotion-aware systems enable in experience personalization. Indeed, emotion-aware systems can be used to boost the user's intrigue, motivation, and engagement, while minimizing negative emotions, such as boredom, that may damage the current activity. For example, when a emotion-aware system senses that a user feels boredom during a writing task [3], it can provide proper support to help reducing boredom and thereby increasing engagement, which is a prerequisite for reaching the flow state in the activity at hand [4].

While emotion-aware systems have been constructed to detect and act upon various emotions [5–14], there is one emotion – boredom – which has gained relatively little attention from researchers. One possible reason for this, as Pekrun et al. [15] suggest, is that boredom is "*an inconspicuous, 'silent' emotion, as compared with manifest affective states like anger or anxiety*". Moreover, boredom is a complicated emotion; a bored person can exhibit either high or low arousal [16]. Because of these reasons, elicitation and detection of boredom can be remarkably more demanding than those of more explicit and uncomplicated emotions.

There are three motives for us to choose boredom as the target emotion in this study: (i) boredom can disrupt an activity, such as learning, by preventing focused attention; (ii) boredom may have a negative effect on motivation; and (iii) boredom is a complex emotion, which has attracted comparatively low amount of attention in previous emotion detection research using physiological measurement. Due to these reasons, boredom is an important target emotion for future emotion-aware systems to manage.

Boredom detection methods – and emotion detection methods in general – can be divided into three groups: psychological,

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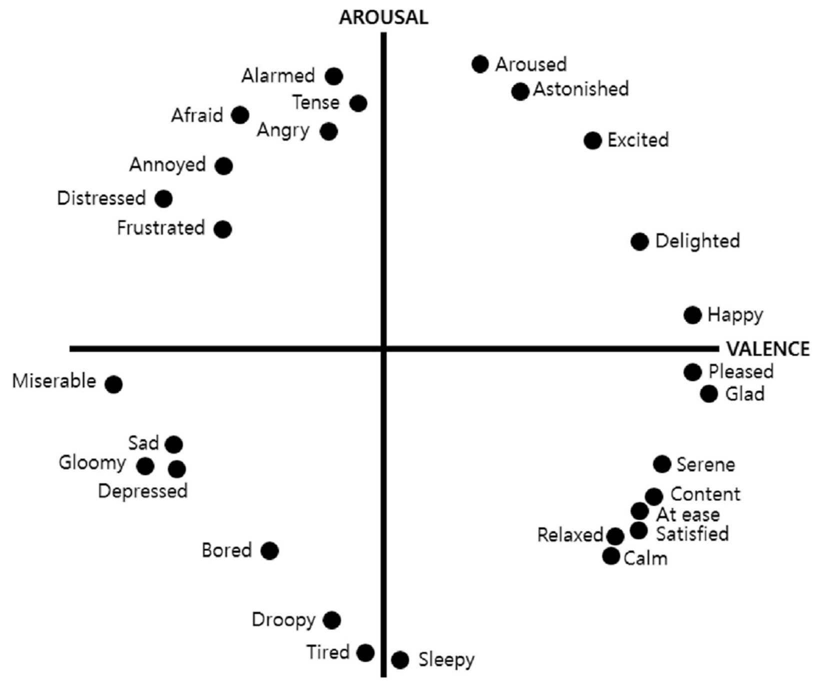

Fig. 1. The Circumplex Model [28].

physiological and behavioral [17]. In this study, we focus on the physiological boredom detection, which concerns measuring various physiological aspects of a participant's response to a stimulus. There have been studies which attempted to detect boredom by physiological methods [18–22], with some of them focusing specifically on the use of eye tracker [23] or electroencephalogram (EEG) [24]. To the best of our knowledge, however, there is a gap in the current understanding of whether there exists a connection between eye gaze and EEG signal when people feel bored.

The purpose of this study is to fill this gap by investigating the relationship between eye gaze and EEG in the context of boredom. We set three hypotheses to frame the study. First, when people get bored, they lose attention to the task at hand [25]. Secondly, when they get bored, their EEG data and gaze data may show distinctive patterns compared to the expected state (e.g. stable EEG, eye fixation at an expected location). Third, due to the first and second hypotheses, a correlation may exist between gaze data and EEG data when people feel bored. Before verifying these hypotheses in an experiment, we first provide explanations of the theoretical underpinnings of emotion modeling and boredom, as well as previously applied methods for collecting and analyzing physiological data for boredom detection. Then, we proceed to present the design and the results of a boredom detection experiment using a video stimulus, an eye tracker, an EEG sensor, and a questionnaire. We designed the video stimulus to be a generic boredom inducing tool that could be used later in other studies related to boredom.

2. Background

2.1. Emotion models

Some researchers developed emotion-aware systems by hand-picking certain emotions [6] or by using dubious terms to express emotions [26]. Such practices can pose validity challenges. Firstly, if the terminology for expressing emotions is not well established, researchers might end up choosing inappropriate terms that may be misunderstood or terms that are not emotions at all. Secondly, the conceptual distance between emotions remains ambiguous if emotions are not represented through an appropriate model. To alleviate these challenges, scientifically validated emotion models have been developed that can be used to classify emotions in emotion-aware systems. Essentially, an emotion model is a structure in which various emotions are categorized according to some criteria. Emotion-aware system developers can utilize emotion models for unambiguous classification of emotions.

Most emotion models have foundations in psychology. Already in 1897, Wundt [27] proposed three dimensions through which emotions can be mapped: "*pleasurable or unpleasurable*", "*arousing or subduing*" (exciting or depressing), and "*strain or relaxation*". In 1980, Russell proposed the Circumplex Model (Fig. 1) in which emotions are distributed in a two-dimensional circular space on two axes: arousal and valence [28]. Arousal on the vertical axis represents the level of excitement (relaxed or aroused) and valence on the horizontal axis indicates the level of emotional state (positive or negative). The Circumplex Model has been used to classify participants' emotions in studies covering various fields [24,29–31].

Russell's Circumplex Model is often used as the basis for emotion-related research but it is not the only emotion model available. According to Grandjean et al. [32], there are three types of emotion models. The models of Wundt and Russell belong to dimensional models, which categorize emotions using various dimensions, such as pleasant–unpleasant, excitement–inhibition and tension–relaxation. Another type is basic emotion models, also known as the Discrete Emotion Theory, which define a set of emotions that form the base of all other emotions. The number of basic emotions vary among these models. For example, Ekman proposed six basic emotions: anger, disgust, fear, happiness, sadness, and surprise [33]. Stevenson et al. used a basic emotion model to prove that the words in Affective Norms for English Words (ANEW) are effective to elicit discrete emotions [34]. ANEW is a set of English words which were rated in terms of valence, arousal and dominance [35]. The third type of emotion models is componential appraisal models, which suggest that our internal state and the state of the world surrounding us are used as inputs for a continuous emotion generation process in our brains [32,36]. Scherer et al. [37] applied an appraisal-based model for mapping of facial expression mechanisms to different emotions to prove the effectiveness of the model.

2.2. Boredom

2.2.1. Defining boredom

Boredom is a complex emotion that is difficult to define, and therefore to elicit and detect, in a simple manner. As the following examples demonstrate, researchers have attempted to define boredom in various ways, which may not be fully compatible. In Russell's Circumplex Model, boredom is among the emotions placed in the third quadrant with low arousal and low valence, thus indicating a negative passive state [28]. Fahlman et al. [16], whose study focused solely on boredom, concluded the following definition of boredom based on a literature review: "*boredom is the aversive experience of having an unfulfilled desire to be engaged in satisfying activity*." They further listed several manifestations of boredom as follows: (i) lack of engagement, (ii) low arousal, negative valence, (iii) high arousal, negative valence, (iv) experiencing a slow passage of time, and (v) difficulty of focusing attention. Attention (or lack of it) has been identified as a key component of boredom. Based on their analysis of previous boredom studies, Eastwood et al. [25] defined boredom in terms of attention, proposing that boredom occurs when we are (a) not able to focus our attention to information (internal or external) required for participating in satisfying activity, (b) are focused on the said inability to focus our attention, and (c) attribute the cause of our state to the activity (e.g. "this lesson is boring!"). These definitions demonstrate that although boredom can have many manifestations, it is a major threat to the flow experience [4] where persons pay full attention to a satisfying activity to such extent that they may lose the track of time.

It is noteworthy that both Russell [28] and Fahlman et al. [16] incorporate the dimension of arousal in their definitions of boredom, but the only latter recognizes that a bored person can also exhibit high, agitated arousal. Whether a bored person's arousal is high or low may depend on their trait boredom, i.e. their tendency of becoming bored, which is described next.

2.2.2. Trait and state boredom

There are two types of boredom that researchers have used in their studies depending on the research purpose. The first type is *trait boredom*, which is the tendency of an individual to become bored [16]. While trait boredom is more concerned with the personality of the individual rather than the state of boredom they experience in certain situations, researchers like Farmer and Sundberg [38] have measured trait boredom to understand how participants react when they feel bored. The second type is *state boredom*, which is a transitory emotion with a relatively short timespan [39]. State boredom is the emotional state that people experience when they say "I am bored". Fahlman et al. [16] recognizes a difference in the source determinant between trait and state boredoms: trait boredom is typically strongly determined by internal psychological characteristics, whereas state boredom's determinant often comes from an external situation. In this study, we seek to detect the occurrence of boredom through physiological sensors when participants watch a video stimulus, i.e. an external factor. Thus, we treat the boredom as a state rather than a trait.

2.2.3. Attention and boredom

There exists a relationship between state boredom and a person's attention to the activity at hand. Fahlman et al. [16] divided the theories of boredom into four distinct groups – psychodynamic, arousal, attention and existential – and made the following conclusion on the attention group (i.e. attentional theories) based on their review of Fisher [40]'s and Hamilton [41]'s research: "*boredom is caused by a failure of attentional processes resulting in an inability to focus or engage attention*". This definition refers to the existence of a relationship between boredom and attention, which has been proven through task-performance using self-reporting [15,16,42]. These previous studies showed that when people become bored, they start to lose their attention, and their current activity will eventually be disturbed due to lack of attention. We devised our hypotheses and experiment based on the relationship between attention and boredom, as lost attention can be considered to be a possible sign of boredom.

2.3. Detecting boredom

Although there have been many studies on the topic of emotion detection [5,6,7–13,14], boredom has attracted relatively little attention due to its multidimensional manifestations (e.g. high and low arousal), as we have shown in the previous section. Moreover, as Pekrun et al. [15] pointed out, boredom is a "*silent*" emotion in that it is manifested through subtle signs, whereas other emotions, such as anger or fear, exhibit more clear signs of how the person feels. Due to the aforementioned properties, boredom is a difficult emotion to detect. However, there have been some studies attempting to do this, as we show in this section.

Although emotions can be detected by various ways in research, it is possible to identify common factors in them. Feidakis et al. [17] divided emotion detection methods into three categories: psychological (subjective), physiological and behavioral. In the following, we explain these categories with examples from boredom detection literature.

In psychological methods, participants self-report their emotions using instruments such as verbal feedback, questionnaires and pictorial scales. For example, Farmer and Sundberg [38] and Fahlman et al. [16] developed and validated psychological methods where participants had to answer a questionnaire to measure trait boredom and state boredom, respectively. Psychological measurement is often combined with other methods (e.g. physiological measurement) to verify and strengthen the results.

In contrast to psychological methods that may suffer from subjectivity, physiological methods strive for objectivity by using sensors to capture physiological signals from participants and analyzing the captured data to detect emotions. For example, Mandryk and Atkins [18] used galvanic skin response (GSR), electrocardiography (ECG), and electromyography (EMG) to collect participants' physiological signals for emotion detection while they played a video game.

Similarly to physiological methods, behavioral methods may also utilize sensors and other devices, such as microphone, camera, keyboard and mouse, but the purpose is to detect emotions by analyzing participants' behavior and activities. The data analysis is performed by a person who has expertise in behavioral analysis. Facial expressions and body gestures are examples of target behaviors that are often used in behavioral emotion detection. For example, since Ekman [43] proposed that a relationship exists between emotions and facial expressions, researcher have built systems to detect boredom by analyzing facial expressions and posture patterns from a camera feed [19].

In this paper, we explore boredom detection using physiological data, i.e. we focus on participants' bodily functions. A post-stimulus questionnaire is also used to verify the existence of boredom. In the following section, we review previous work on approaches that have been used for boredom detection via collection and analysis of physiological data.

Table 1
Physiological data sources and data types used for boredom detection.

Data source	Data type
Heart	Heart rate (HR) [18,24]
	HR variability [18]
	Electrocardiography (ECG) [20–22]
Skin	Electrodermal activity/Galvanic skin response [18,24,20–22]
Face	Facial expressions [19,18]
Gesture	Body gestures [19]
Blood	Blood pressure [24]
	Photoplethysmography (PPG) [20]
Brain	Electroencephalography (EEG) [24]
Eyes	Gaze, fixation point, saccade [23]

Table 3
EEG brain waves (based on [24]).

Brain wave	Frequency range	Occurrence
Delta	0–4 Hz	Sleep
Theta	4–8 Hz	Going to sleep
Alpha	8–13 Hz	Relax, calm, thinking
Beta	15–40 Hz	Focus, alert, mental work, anxiety

2.4. Related work on boredom detection

The previous boredom detection studies presented in this section followed a hypothesis that a certain aspect in the participant's physiology changes when they feel bored. Tables 1 and 2 list these previous studies that aimed to detect boredom, and in some cases also other emotions, using various physiological data sources and data analysis methods, respectively. Each data source, in turn, can have one or more data types. For instance, we can measure gaze positions, gaze durations and pupil sizes from eyes. It is an important observation that these previous studies utilized multiple data sources to detect boredom, with possible reasons being to increase reliability and to detect multiple emotions. In the following sections, we explain how these data sources were previously used for boredom detection, with a focused attention on current evidence using the brain and eyes because they are used in our experiment in Section 3.

The human brain generates electrical signals, referred to as brain waves, at multiple frequencies. These signals can be collected by electroencephalography (EEG) in which electrodes are attached to the scalp. EEG data is typically handled in time domain but it is sometimes transformed to frequency domain depending on the desired analysis method. Table 3 illustrates EEG data in terms of brain wave types together with respective frequencies and situations in which the brain waves are known to be generated. EEG data has been actively used for analyzing the brain's functionality, including detection of various emotions [5,24,44–46].

In their study, Shen et al. [24] measured and analyzed EEG and other data sources to detect several target emotions, with one of them being boredom. The detection was done by extracting power densities of alpha, beta, theta, delta, and gamma frequency bands as features, and then feeding the features to Support Vector Machine (SVM) and k-Nearest Neighbors (kNN) algorithms for building a classification model. As results, the researchers achieved 67.1% and 62.5% accuracies for boredom detection with the two algorithms, respectively.

Eyes are said to be the mirror to one's soul. While this may or may not be true, research has proven that eyes certainly are the mirror to one's emotions. In addition to EEG data, eyes have been used as a data source in emotion detection research [5,8,10,13,45,46], including also boredom [23]. Jaques et al. [23] used an eye tracker to collect various types of eye-related data, such as gaze position, fixation point and saccade. Moreover, they defined contiguous areas that are of interest in terms of focused attention. These areas are known as Areas of Interest (AOIs), and more than one AOI can be defined for a single stimulus depending on the experiment's purpose. Jaques et al. [23] applied SVM, Naïve Bayes and Logistic Regression algorithms to analyze the data for boredom detection.

Skin data used for emotion detection typically comprises electrodermal activity (EDA) of the skin. The amount of skin's EDA changes depending on the body status (e.g. sweating). In particular, an EDA property called Galvanic Skin Response (GSR) has been used for boredom detection. GSR data are collected by attaching two electrodes to the skin in close proximity to each other, and then measuring how much of a weak electric current passes from one electrode to another. Previous research results suggest that a correlation exists between the amount of EDA and boredom [18,20–22,24].

Visual analysis of facial expressions is a common method for humans to interpret how their peers feel. Following this idea, some researchers have chosen facial expressions as a source for boredom detection [18,19]. These studies used two different methods capturing facial expressions: image recognition and measurement of facial muscle tension. The image recognition method analyzes a facial photograph to measure the shapes of facial elements, such as eyebrows, eyes, nose and mouth [19]. The facial muscle tension measurement method is more obtrusive, as it requires attaching electrodes to the participant's face [18].

Heart rate was used to detect boredom and other emotions among the surveyed studies [18,24]. It can be directly collected by measuring cardiovascular activity through electrodes on the chest, or indirectly computed from other data, such as blood pressure and light sensor readings of the fluctuations in capillaries. Moreover, ECG, where electrodes attached to chest give precise information about the function of the heart, has been combined with other physiological sensors to detect boredom [20–22].

There are also other physiological data sources that have less frequently been used for boredom detection. For example, blood pressure [24] and blood volume changes [20] have been identified as potential data sources. Furthermore, the relationship between a person's physical movement and boredom has been explored by analyzing body gestures [19].

Table 2
Analysis methods used for boredom detection.

Study	Data source	Analysis method
Mandryk and Atkins [18]	Heart, skin, face	ANOVA, Fuzzy logic
D'Mello et al. [19]	Face, gestures	Neural Network
Shen et al. [24]	Blood, brain, skin, heart	Support vector machine
Jaques et al. [23]	Eyes	Support vector machine, Naïve Bayes, Logistic regression
Jang et al. [20]	Heart, skin, blood	Discriminant function analysis, linear discriminant analysis, classification and regression trees, self-organizing map, Naïve Bayes, support vector machine
Giakoumis et al. [21]	Heart, skin	Linear discriminant analysis, sequential backward search
Giakoumis et al. [22]	Heart, skin	Kendall's tau correlation coefficient

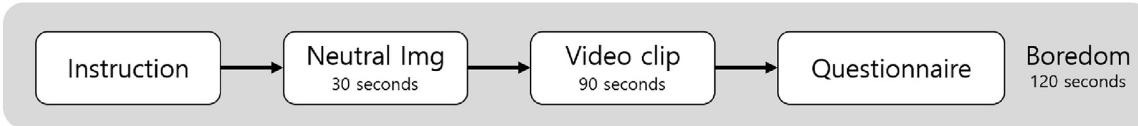

Fig. 2. Experiment protocol.

3. Experiment

In this section, we describe an experiment for detecting state boredom from gaze and EEG data. We start by presenting the experiment design followed by the achieved results.

3.1. Experiment design

3.1.1. Stimulus and protocol

The purpose of our experiment is to elicit boredom from participants in a relatively short time. To achieve this, we built an experiment protocol that is illustrated in Fig. 2. The experiment duration (120 s) is the minimum length; the actual duration depends on how much time the participant spends on reading instructions and answering the questionnaire.

The experiment uses a video stimulus that we designed to elicit boredom in a short time. Before the experiment, the participant is informed about the voluntary nature of the experiment and that they could stop the experiment at any time. Then the participant signs a consent form and reads an instruction page that explains the process of the experiment. Before being exposed to the stimulus, the participant looks at an image of a cloud (Fig. 3a) for 30 s, with the purpose of setting the baseline emotion as neutral. The cloud image was acquired from the International Affective Picture System (image ID: 5870), which was proposed and validated by Lang et al. [47]. The image in Fig. 3a is an approximation of the original IAPS image due to copyright restrictions. After the neutral image, a video stimulus is played for 90 s during which a small circle moves in the clockwise direction on the outline of a bigger circle (Fig. 3b). The small circle slowly completes one lap during the play time. The purpose of the slowly moving circle animation is to elicit boredom in a generic way without relying on any specific genre of content that might affect participants in different ways. After watching the video stimulus, the participant completes a questionnaire to answer how strongly, on the scale of 1–9, they felt boredom. Thus, the experiment protocol comprises both physiological measurement (sensors) and subjective, confirmatory measurement (questionnaire).

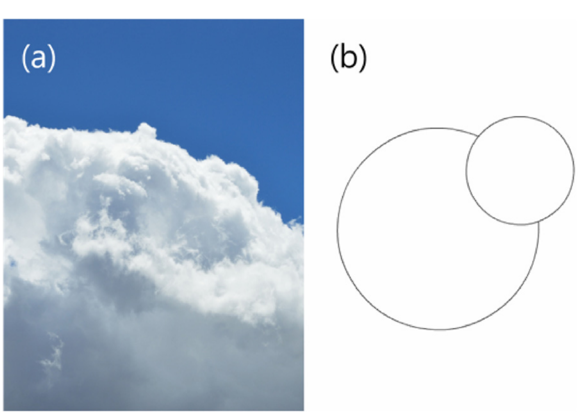

Fig. 3. (a) Neutral image, (b) video stimulus.

Table 4
Data types supported by the physiological data acquisition system.

Data type	Source device
Facial expression	Web Camera
Voice	Microphone
Eye gaze, pupil size	Eye Tribe eye tracker
Heart rate, skin temperature	Microsoft Band wristband
EEG	Muse headband (4 electrodes)
Electromyography (muscle tension)	Myo armband × 2
Head movement	Eye Tribe eye trackerMuse headband
Hand movement	Microsoft Band wristband
Galvanic skin response	Grove GSR sensor on Arduino

3.1.2. Physiological data acquisition system

We created a system that can acquire data from various physiological data sources in a centralized and synchronized manner. The primary motivation for the system was to easily collect data from multiple sources during experiments involving physiological measurement. Table 4 lists the sensors and data types that are currently supported by the system, with those used for this experiment highlighted.

Another motivation for developing the data acquisition system was to enable automatic execution of customizable experiment protocols. To meet this goal, our system provides a protocol editor which allows researchers to customize, order and schedule instructions, stimuli, and questionnaires in an experiment. Because data acquisition is controlled by a single system, we can achieve time synchronization among recorded data and presented content.

The data acquisition system has two displays showing graphical user interfaces for the participant and the experiment monitor, respectively. The participant's display shows instructions, stimuli and questionnaires. The experiment monitor's display shows the system status, sensor connection quality and raw data values collected from sensors at run time, thus allowing data quality inspection. The participant cannot see the experiment monitor's display during the experiment.

In this study, we focused on collecting and analyzing EEG data and eye gaze data. The sensor devices were selected on the basis of affordability to enable future emotion-aware system development at a reasonable cost. For capturing EEG data, we used the Muse headband, a commercial EEG sensor capable of capturing EEG data from four points (FP1, FP2, TP9, TP10) of the scalp simultaneously. The data sampling frequency is 220 Hz with the range from 0.0 to 1682.815 μV. For collecting eye gaze data, we used the Eye Tribe eye tracker which has the frame rate of 30 fps. It collects both eyes' gaze positions on the screen with timestamps.

3.1.3. Participants and procedure

We collected data from 9 male and 8 female participants having 22–33 years of age (average: 27.4). Of all participants, 11 (4 male, 7 female) were Korean students and university staff members, and 6 (5 male, 1 female) were international students. The participants were normal healthy subjects and all of them were right-handed.

There are three reasons as to why the number of participants is only 17. First, we ran the experiment during a semester break, thus there were not many potential participants available for recruitment. Second, the Eye Tribe eye tracker cannot track well eyes of a person who wears glasses. Third, in South Korea, 96% of young male

Fig. 4. (a) Monitoring researcher viewpoint. (b) Participant viewpoint.

adults had myopia [48] and over 51% of young adults wear glasses [49]. Hence, recruiting a large number of suitable participants at the university was not feasible. To further justify the number of participants in this research, previous studies on emotion detection using EEG and eye tracker sensors were conducted with relatively small numbers of participants; Zheng et al. [46] and Soleymani et al. [5] used 5 and 24 participants, respectively, to verify the accuracy of a multimodal emotion detection method consisting of an EEG sensor and an eye tracker. Moreover, Kapoor et al. [10] implemented a frustration detection system through eye shape, pupil position, eyebrows, body posture and skin conductance signals from 24 participants.

The participants attended the experiment one by one. One researcher assisted the participants during the experiment and interviewed them after the experiment. Another researcher monitored and controlled the data acquisition system. Fig. 4 demonstrates the experiment setup. The participants were informed about the experiment procedure and they were asked for a consent before the experiment commenced. The purpose of the experiment was not revealed to avoid affecting behavior and thinking of the participants.

3.1.4. Data analysis methods

In this section, we describe the methods that were employed to analyze the collected eye tracking and EEG data. Before conducting the analysis, we reviewed the sensor data quality for each participant to judge their eligibility for analysis.

We analyzed the eye tracking data based on a hypothesis that losing attention while watching the video (i.e. losing focus on the moving circle) could indicate boredom. We used heat maps of gaze data to visually identify the regions where the participants lost attention during watching the video, thus confirming that the participants might have been bored. Heat map is a data visualization technique that, when applied to gaze data, shows the participant's gaze positions in different colors that depict how much the participant gazed at the respective areas. Thus, a heat map can indicate where the participant's visual attention has been (or has not been) during an experiment.

Heat maps were created with Ogama (Open Gaze And Mouse Analyzer) [50], an open source software for analyzing eye gaze and mouse data. We used the latest version (5) which provides various analysis tools, such as the fixations module to draw heat maps, the statistics module to compute statistical results, and the replay module to draw the path of eye gaze on a stimulus. The parameters that we used for heat map generation with Ogama are presented in Table 5, as they are reported in the software.

To programmatically analyze the eye gaze data, we used the hitbox technique in each window (1 s). This was done to find out the times and the regions during which the participant lost focus. In the hitbox technique, a region is formed around an AOI (adapted from the work of Eisenbarth and Alpers [13]), which in our case was the small moving circle. Then, the number of hits (i.e. fixation points) that occur within the box are counted.

Table 5
Ogama parameters used for heat map generation.

Parameter information	Value
Screen size of eye tracker monitor (in pixel)	1920 × 1080
Sampling rate	30 Hz
Maximum distance in pixels that a point may vary from the average fixation point and still be considered part of fixation	20
Minimum number of samples that can be considered as fixation	2
Fixation detection ring size. This value sets the size of buffer that is used to detect fixations	31
Merge consecutive fixations within max distance into one fixation	True
Diameter ratio of fixations. The fixation time in milliseconds over this number will give the fixations circle diameter	2

We approached the collected EEG data by a visual analysis method with MATLAB (plot() function)) to identify significant deviations in the signal, which could indicate boredom. To programmatically analyze the EEG data, we also used the thresholding technique and statistical methods, including signal magnitude area (SMA), standard deviation and mean. Purpose of using the thresholding technique with statistical methods was to allow an individual EEG threshold value to be calculated for each participant, thus avoiding fixed threshold values. Similar approaches involving thresholding, mean and standard deviation have also been used in previous emotion detection studies [7,51]. To the best of our knowledge, SMA has not been used for EEG data analysis; however, it is a well known technique for signal processing and it is often used for analyzing time series data, for example to detect changes in the magnitude of inertial sensor data [52,53].

3.2. Results

Here we present the results of our analysis of physiological data (i.e. eye gaze, EEG) collected from the participants during the experiment. Moreover, questionnaire results are shown as a subjective measurement to confirm the existence of boredom. Significant data loss occurred with some participants due to instability of the eye tracker and EEG sensor connections. After removing the data of four participants for this reason, we analyzed the data of the 13 remaining participants (7 males, 6 females).

3.2.1. Physiological measurement

Following our hypothesis that losing attention (i.e. losing focus on the small circle) could be a sign of boredom, we first used Ogama to create heat maps from the eye gaze data that were recorded during the video stimulus playback. Then, we visually analyzed the heat maps to identify the regions where the participants lost focus. The visual analysis was done by overlaying the trajectory of the moving circle on top of the heatmap. Through this overlay, we were

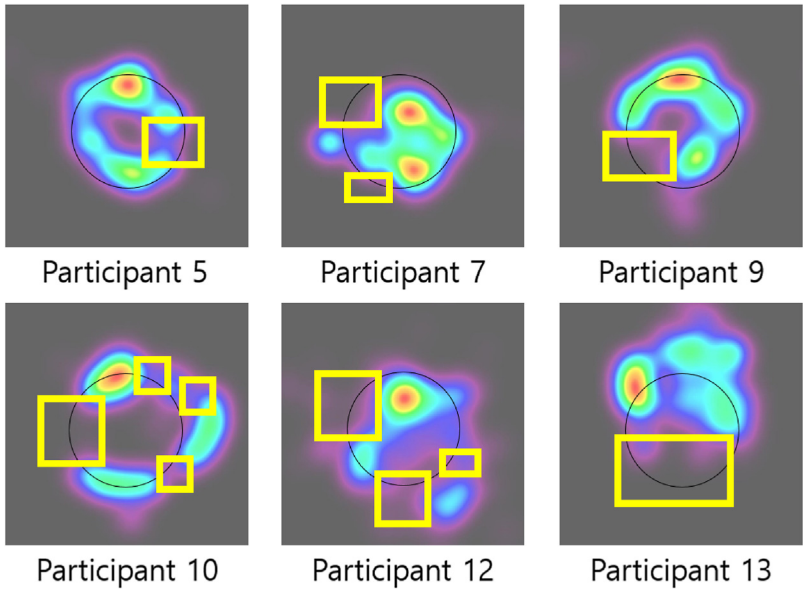

Fig. 5. Lost focus areas in heat maps of six participants. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

able to identify the focus lost areas, as illustrated in Fig. 5, which shows the heat maps for six participants (5 females, 1 male). Red color indicates the areas at which the participant gazed the most; purple color has the opposite meaning. Consequently, we assumed that any gaps in gaze focus, which are marked as yellow squares in Fig. 5, may indicate boredom. By this visual analysis we confirmed that 11 out of 13 participants' heat maps had at least one lost focus area.

Next, we analyzed the EEG data to complement the eye gaze data analysis. We hypothesized that boredom could be confirmed if we can find features in the EEG data that coincide with the gaps found in the gaze data. Following this idea, we first used MATLAB (plot() function) to graphically analyze the EEG data, thus identifying changes in the amplitudes of the participants' EEG signals. In order to programmatically detect these amplitude changes in the EEG data, we applied a modified version of the signal magnitude area (SMA) method, which indicates how much the signal fluctuates by summing the absolute differences between adjacent values within a window. The modified SMA is defined in Formula (1), where x_i is the ith value in a window, and N is the length of the window. The EEG sensor's sampling frequency was 220 Hz and we set the window size (N) to be 1 s:

$$\text{SMA} = \sum_{i=1}^{N-1} | x_{(i+1)} - x_i | \tag{1}$$

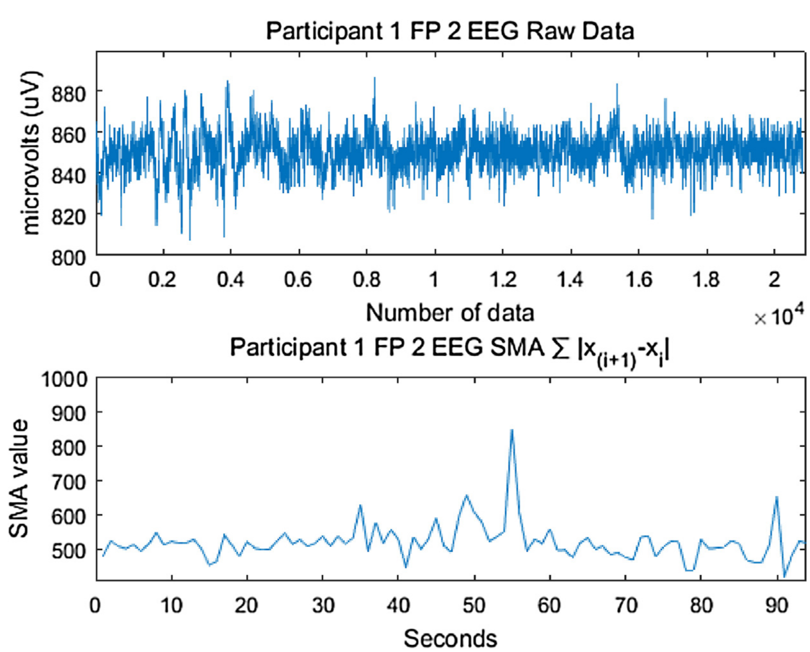

Fig. 6. The EEG signal of one participant before and after applying SMA.

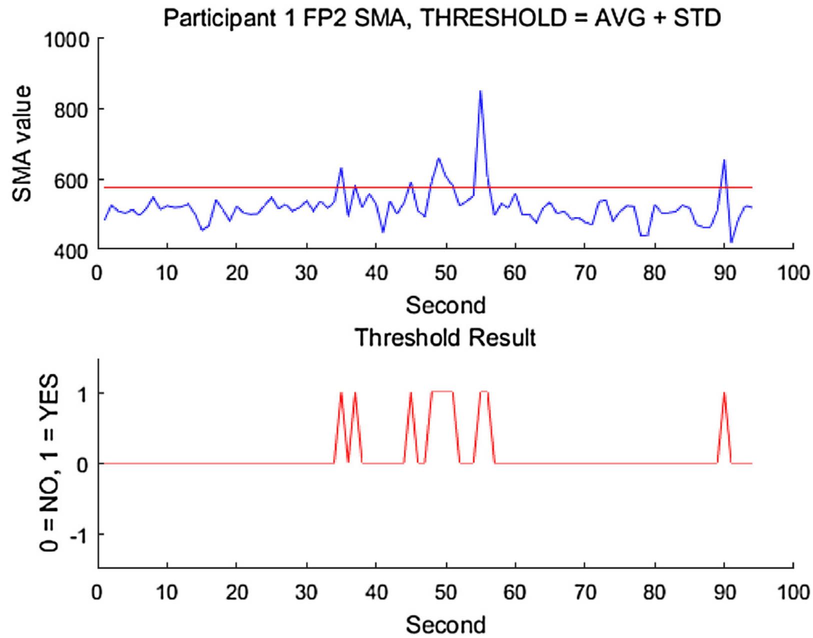

Fig. 7. Threshold-based classification between stable and non-stable EEG.

Fig. 6 demonstrates the result of applying SMA to the EEG signal of one participant, showing that SMA can be used to identify windows where the amplitude of the EEG signal increases sharply. Based on the calculated SMA values, we sought to classify the EEG data using labels: *stable* and *non-stable*, where non-stable indicates potential boredom. We approached this classification task with a threshold method, which sums the average and standard deviation values of SMAs calculated for all windows of a participant's EEG signal (see Formula (2), where x is the participant's number). The reason for calculating thresholds by this method is that each participant has a unique signal, thus applying a fixed threshold value for all participants is not suitable. The sum of the average and standard deviation values of SMAs represents the upper limit of the participant's EEG signal's normal fluctuation range. By applying the formula, we identified start/end window pairs of regions where the EEG signal's amplitude was above the threshold. Fig. 7 illustrates the result of this binary classification for one participant.

$$EEGThreshold_{(x)} = AVG(SMAs_{(x)}) + STD(SMAs_{(x)}) \tag{2}$$

After extracting potential boredom windows from the EEG data with Formula (2), we analyzed the gaze data to identify those windows where lost focus in the gaze data correlates with amplitude changes in the EEG data. Red squares in Fig. 8 illustrate regions where gaps in heat maps correlate with non-stable windows identified from the EEG data. To solve this task algorithmically, we used the hitbox technique to calculate a threshold value for fixations within a window (see Algorithm 1). There are two inputs for this algorithm: (i) EEGData, which comprises pairs of start/end windows from the EEG data indicating the regions where the amplitude is above the EEG threshold (see Formula (2)), and (ii) GazeData, which contains all gaze fixation points. The output of the algorithm is a threshold value for gaze fixation count that can be used to detect windows during which boredom has potentially occurred.

Algorithm 1. Gaze fixation threshold detection algorithm

```
Input: Pairs of start and end windows in the EEG data where the amplitude
       was above the EEG threshold, defined as "EEGData"
Input: Gaze fixation points, defined as "GazeData"
Output: Gaze fixation count threshold
begin
    Define and initialize "Averages" list;
    for each pair of windows in "EEGData" do
        Define and initialize "FixationList" list;
        /* First item of a pair                                          */
        Define and initialize "StartWindow";
        /* Second item of a pair                                         */
        Define and initialize "EndWindow";
        for each window between "StartWindow" and "EndWindow" do
            Define and initialize "Fixations";
            Define "Hitbox" as an area around the area of interest with a buffer
             range ;
            for each fixation point in "GazeData" do
                if the fixation point is inside "Hitbox" then
                    Increase Fixations by one;
            Add "Fixations" to "FixationList";
        Calculate the average of fixations in "FixationList" and add it to
         "Averages";
    Return the lowest value in "Averages";
```

In this algorithm, we set one second as the window size and 0.5 cm as the buffer range around the AOI. The AOI was defined to be the small circle that moves in the clockwise direction on the outline of the bigger circle. The buffer range was set according to the eye tracker device's default error range of 0.5 cm. For each window between a StartWindow and EndWindow pair that are selected from the EEG data, the algorithm counts the number of fixations in a hitbox per window. Then, it calculates the average number of fixations in each StartWindow-EndWindow region, and returns the lowest average as the final result.

The red circles in Fig. 9 depict the regions in heat maps where the detected EEG signal amplitude fluctuations (marked with red

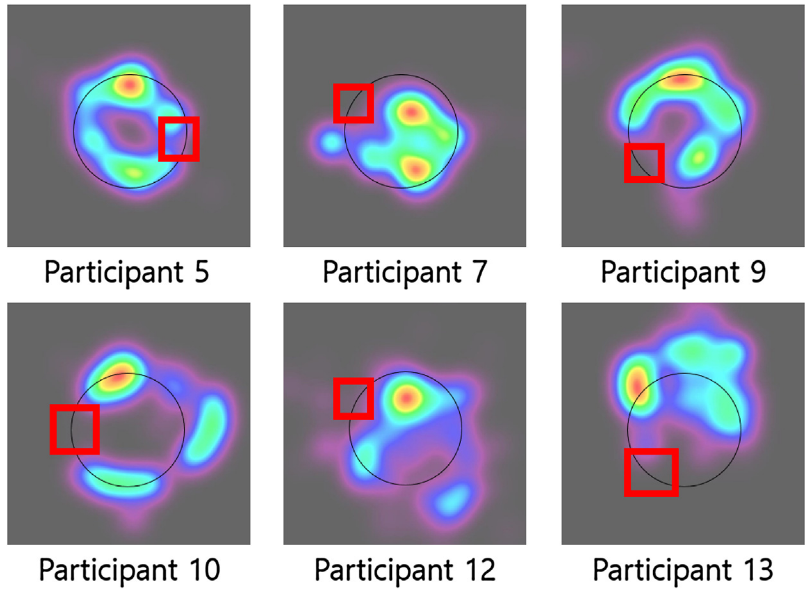

Fig. 8. Correlations identified from heat maps and EEG data for six participants.

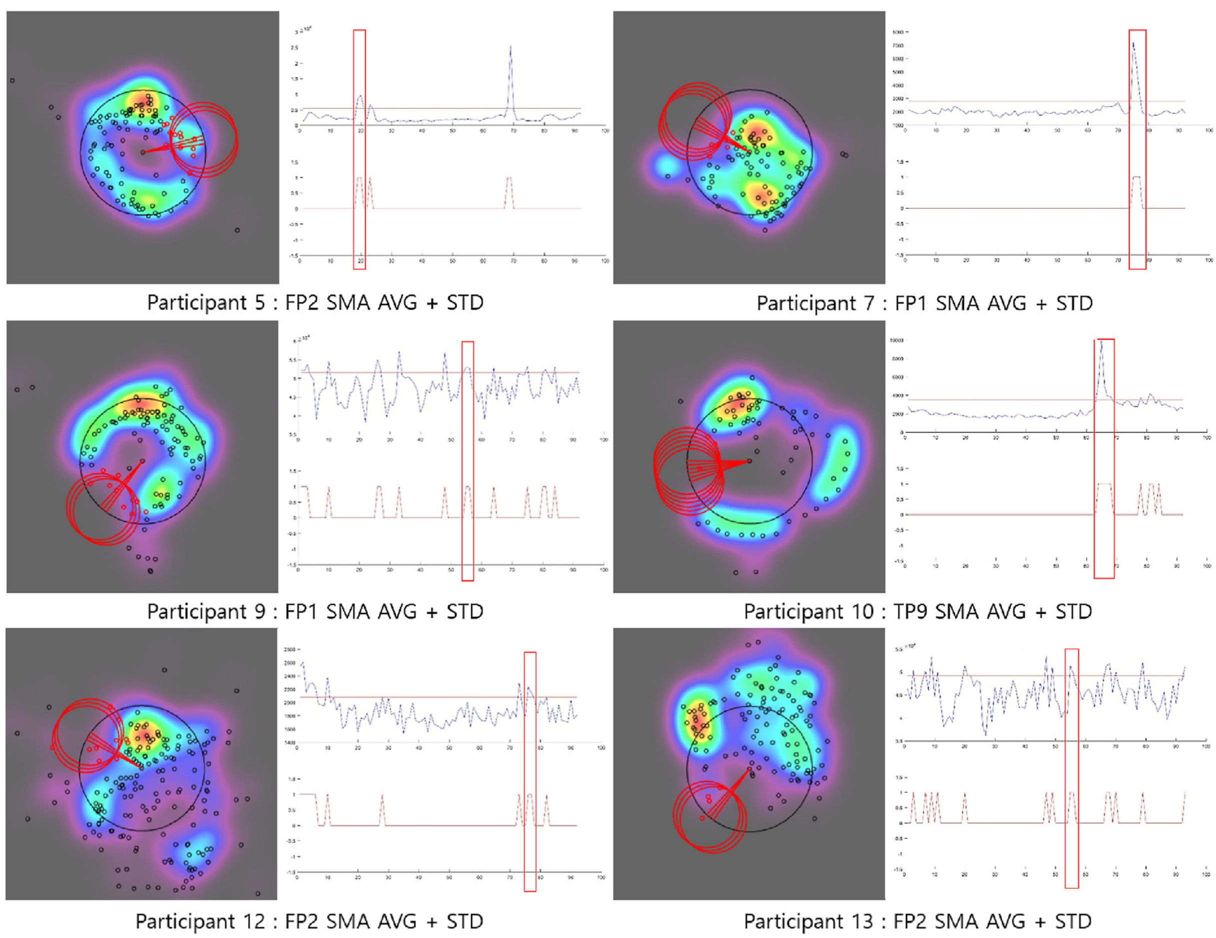

Fig. 9. Correlations among eye gaze and EEG data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

rectangles) coincide with the lowest average numbers of detected fixations by Algorithm 1. We call these regions "Potential Boredom Regions" (PBRs), indicating windows in which the participants might have felt bored.

Table 6 reports the average numbers of fixations in overall gaze data and in PBRs. All participants' average fixation counts in PBRs were lower than 17. Thus, we set the threshold for our video stimulus to 17 to classify whether the participants felt boredom or not

Table 6
Average numbers of fixations in overall data and in PBRs.

Participant	Overall data	PBR	Participant	Overall data	PBR
1	21.49	1	7	13.7	5.33
2	28.13	14	8	11.55	8
3	22.68	15	9	20.76	9.5
4	24.15	16.33	10	12.11	3.4
5	21.55	13.5	11	22.2	13
6	21.64	15.5	12	24.55	11
			13	21.29	4

Table 7
Subjective measurement of boredom.

Participant	1	2	3	4	5	6	7	8	9	10	11	12	13
Answer (1–9)	2	3	8	6	8	6	8	7	7	8	7	6	7

while they were watching the video stimulus. We identified that all participants had PBRs in their data. However, for three participants (7, 8, 10), the average numbers of fixations for the overall data were lower than the threshold.

3.2.2. Subjective measurement (questionnaire)

After watching the video stimulus, the participants answered a questionnaire about how bored they felt on a scale of 1–9, where 1 means that the video was not boring at all and 9 means that it was extremely boring. The answers to this subjective evaluation in Table 7 indicate that 11 participants answered over 6 while only two participants answered less or equal than 3. The mean of 13 participants' answers is 6.38, and the frequencies for the answers 2, 3, 6, 7 and 8 are 1, 1, 3, 4, and 4, respectively.

From these results we can conclude that all participants felt boredom at some level. To gain a deeper insight, we attempted to find whether correlations exist between the questionnaire results and the features extracted from the eye gaze and EEG data (e.g. SMA values, mean and standard deviation values of fixation counts in PBRs and windows). However, our analysis results revealed no significant correlations.

4. Discussion

The motivation for this study stems from the fact that boredom is a negative emotion that can cause disturbances to an activity. When an emotion-aware system detects boredom in the user, it can take appropriate actions to remove or diminish the negative emotion. For example, as Feidakis et al. [17] suggested, an emotion-aware system could provide pleasurable things that can help the user remove boredom from their minds. Moreover, user engagement and task effectiveness can be improved if the system provides appropriate interventions to recapture the user's attention when they feel bored.

We presented the design and the results of an experiment that aims at eliciting boredom through a video stimulus. Our first hypothesis was that losing focus while watching the video could be a sign of boredom. Based on an initial visual analysis of heat maps, we inferred that eleven participants lost their focus, thus prompting for a more analytical approach.

Our second and third hypotheses suggested patterns within and a relationship between EEG and eye gaze data when people feel bored, respectively. These hypotheses were confirmed by our data analysis that revealed temporal correlations between the patterns identified within the EEG data and the eye gaze data for all participants. In the fixation threshold detection algorithm results (Table 6), all participants showed lower than 17 of the average number of fixations in PBRs. Therefore, we declared the boredom detection threshold for the video stimulus to be 17. By using this threshold together with the EEG classification threshold, we are able to detect boredom from participants who are watching this particular video stimulus.

The fixation threshold detection algorithm can be adapted to other scenarios that use a stimulus on the screen with a well-defined AOI for identifying lack of focus (i.e. possible sign of boredom). First, a hitbox area and a buffer range specific to the stimulus must be defined. Then, training data must be collected, from which a fixation threshold value can be extracted with the algorithm. The threshold, in turn, can be used to detect PBRs in gaze data. However, identified PBRs should not be declared as boredom without additional evidence. Therefore, we suggest that another method, such as psychological measurement, would be used to verify the result.

According to the subjective measurement conducted via a questionnaire, boredom was elicited successfully as 84.62% of the 13 participants answered over 6 (on the scale of 1–9) for boredom and the mean of all answers was 6.38. There were two participants (1 and 2) who answered three or less for boredom in the questionnaire even though their data revealed PBRs. We can thusly conclude that the monotonous video stimulus having a running time of 1 min 30 s was enough to elicit boredom in all participants. However, we cannot expect that everybody has the same threshold for boredom, not to mention similar levels of trait boredom, and such individual differences are something that emotion-aware system developers should consider. Moreover, there are other factors, such as age, culture, fatigue and state of mind, that may affect the learner's tolerance for boredom.

Although our study revealed that all participants felt bored at some level, we could not identify significant correlations between the questionnaire results and the physiological data. To conduct a deeper correlation analysis, we propose a control group - experiment group study in the future where only the former is exposed to the boredom stimulus.

In the case of three participants (7, 8, and 10), the average number of fixations in overall gaze data was lower than the identified boredom threshold (Table 6). One reason for this result could be that our algorithm did not consider the lengths of fixations. Therefore, some participants might have stared at a few areas instead of closely following the stimulus, thus decreasing the total number of fixations whilst increasing their lengths. To improve our fixation threshold detection algorithm, we could use the length of fixation as an additional feature and assign weights to each feature (i.e. number of fixation, length of fixation). Despite low numbers if fixations, the three participants had correlations between their EEG and gaze fixation data, and the mean of their questionnaire answers was 7.7, thus clearly indicating boredom.

We analyzed the EEG data with visualization and thresholding techniques, but we did not perform a detailed analysis of alpha, beta, theta and delta waves, each of which carry a different meaning in the brain's functionality. To analyze brain waves independently from each other, we, as computer scientists, must collaborate with neuroscientists to understand how different parts of the brain work and what kind of methods are suitable for analyzing brain waves. Such collaboration could also help us understand the reasons behind the amplitude changes found in participants' EEG data.

The study has limitations that are worth noting. First, although the sample size of 17 is similar to those of some previous studies, more data is needed to thoroughly verify the achieved results. Second, our experiment assessed only state boredom while disregarding trait boredom; the latter may have an effect on threshold calculations for individual participants. Third, the questionnaire was administered at the end of the experiment so the participants did not indicate the point of time when they felt bored. This information could be used to pinpoint the moment of boredom, thus verifying the discovered PBRs. Fourth, although the experiment results are satisfying, they were acquired with affordable consumer-oriented hardware (Eye Tribe, Muse), which may be inferior to expensive research instruments in terms of robustness, accuracy and reliability. For better results, higher quality equipment should be used.

As future research on this topic, we seek to conduct another experiment that focuses on the following aspects: (i) increased number of participants in an experiment group and a control group to reinforce the findings of this study, (ii) subjective measurement of the exact time of boredom (e.g. an indicator button) to ensure that the discovered PBRs are valid, (iii) measurement of trait boredom (e.g. with a questionnaire) to be supplied as a parameter to our boredom detection method, and (iv) different stimulation content to verify that the proposed method can be generalized.

5. Conclusion

Emotion-awareness – and affect-awareness in general – is the next phase in the evolution of personalized computing. Emotion-aware systems can personalize experiences based on the user's emotions. With this study, we contributed to the body of scientific knowledge on emotion-awareness by proposing and executing an experiment for detecting boredom. To better understand boredom as an emotion and methods for detecting it, we started by reviewing previous research related to emotion modeling, boredom and its detection using physiological sensors. Then, we built a data acquisition system that synchronizes access to various sensors, and designed and conducted an experiment to elicit and detect boredom.

The results of our experiment are encouraging, as we found correlations between participants' eye gaze and EEG data with high accuracy. These correlations, although achieved with a relatively small sample, shows a potential for using eye gaze and EEG data in boredom-aware systems. Although the results of a questionnaire-based subjective evaluation confirmed the presence of boredom among participants, further research is recommended for understanding the nature of the detected correlations.

The proposed gaze fixation threshold detection algorithm can be generalized to other use-cases by customizing the hitbox area for a particular stimulus. While this approach works well with stimuli having well-defined AOIs, it may not be easy to define hitboxes for dynamic stimuli where the participant's focus can be expected to be in multiple alternate areas. Thus, more experimentation is needed to identify the types of stimuli for which the hitbox technique can be used and suitable methods for dynamically assigning the hitbox.

Despite a relatively small sample size, these results contribute to the understanding of the correlation between eye gaze and EEG when people feel bored. To the best of our knowledge, there is no previous research focusing on both eye gaze and EEG to find clues of boredom. Our experiment design and analysis results can be used as a starting point for further research on emotion-aware systems which are based on eye gaze and EEG data. In particular, researchers can use these results to find more effective methods for detecting learners' emotions, with the ultimate goal being development of unobtrusive and affordable emotion-aware systems. Finally, the video stimulus created for this experiment is a novel contribution to the area of experiment design, as it aims to be a generic tool for boredom elicitation.

In addition to conducting a future experiment as described in Section 4, we seek to utilize machine learning for in-depth data analysis, which could help us discover more useful features and correlations among data sets of various physiological data sources supported by our physiological data acquisition system. Moreover, we plan to utilize the data acquisition system for other human-computer interaction experiments beyond emotion detection.

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