Experimental Setup and Protocol for Creating an EEG-signal Database for Emotion Analysis Using Virtual Reality Scenarios

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Abstract: Automatic emotion recognition systems aim to identify human emotions from physiological signals, voice, facial expression or even physical activity. Among these types of signals, the usefulness of signals from electroencephalography (EEG) should be highlighted. However, there are few publicly accessible EEG databases in which the induction of emotions is performed through virtual reality (VR) scenarios. Recent studies have shown that VR has great potential to evoke emotions in an effective and natural way within a laboratory environment. This work describes an experimental setup developed for the acquisition of EEG signals in which the induction of emotions is performed through a VR environment. Participants are introduced to the VR environment via head-mounted displays (HMD) and 14-channel EEG signals are collected. The experiments carried out with 12 participants (5 male and 7 female) are also detailed, with promising results, which allow us to think about the future development of our own dataset.

1 INTRODUCTION

Emotions play a significant role on the cognitive processes in human including, motivation, perception, creativity, attention, memory, reasoning, learning, problem solving and decision-making (Hosseini et al., 2015).

There is great interest in developing automatic systems that are capable of automatically recognizing the emotion that a subject is feeling by analyzing one or more parameters, that can range from postural and gestural characteristics to physiological signals. The applications of these systems are very varied, ranging from web site personalization, neuromarketing, education and games to health care, especially mental disorders.

The design of systems for automatic emotion recognition (ER) is a complex problem involving several areas of knowledge such as artificial intelligence, physiology, psychology, etc.

Human emotions involve complex interactions of subjective feelings, as well as physiological and behavioral responses triggered primarily by external stimuli subjectively perceived as “personally meaningful”. Therefore, the emotions can be analyzed using different approaches (Tyng et al., 2017): (1) subjective approaches that assess feelings and subjective experiences, (2) behavioral responses from facial expressions (Song, 2021), vocal expressions (Lausen and Hammerschmidt, 2020) and gestural changes (Sapiński et al., 2019) and (3) objective approaches through different physiological responses that can be objectively measured by neuroimaging and biosensors.

Physiological responses include the electrical and hemodynamic activities of the central nervous system (CNS) which consist of the brain and the spinal cord (Calvo and D'Mello, 2010) and autonomic nervous system (ANS) responses, such as heart rate, respiratory volume/rate, skin temperature, galvanic skin response, cerebral blood flow and electrooculographic signals (Apicella et al., 2021; Pan et al., 2006). Physiological responses of the CNS and ANS are more difficult to consciously conceal or manipulate compared to subjective and behavioral responses.

Many ER systems focus on the study of the brain

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signal since emotions arise from activations of specialized neuronal populations in several parts of the cerebral cortex (Šimić et al., 2021). Brain signals can be measured by various techniques such as Positron Emission Tomography (PET), Magneto Encephalography (MEG), Near Infrared Spectroscopy (NIRS), Functional Magnetic Resonance Imaging (fMRI), Event Related Optical Signal (EROS) and Electroencephalogram (EEG), the latter offering the best temporal resolution.

EEG is a method of neurophysiological exploration based on the recording of brain activity through sensors that translate bioelectrical activity into electrical current. It allows the measurement of voltage fluctuations resulting from the ionic current of the post-synaptic potentials of neurons. For the electrical signal to be detectable, a complete set of neurons must be activated in synchrony to generate a sufficiently strong electric field. EEG-based ER systems have received wide attention in recent years compared to other physiological measurements because acquisition of EEG signals can be easily performed using non-invasive techniques and that EEG signals are highly sensitive to external stimuli.

To develop an automated system, it is essential to train the system using a labelled database. To obtain these databases, emotion induction experiments are used to elicit emotional states to a subject under controlled conditions in which the subject is evoked a certain emotion through external stimuli while one or more signals are recorded. The emotion that is labelled to the recorded signals usually corresponds to the emotion that the subject reports having felt after the experiment, usually by means of a self-assessment sheet based on a mannequin or a score.

One of the most important parameters in the experimental protocol design is the selection of the elicitation mechanism. The most common stimuli are audio-visual type, which consist of listening to sounds and/or viewing images or films passively. However, in recent years, several authors have investigated the use of virtual reality (VR) as a medium to elicit emotions (Baños et al., 2012; Brundage et al., 2016; Riva et al., 2007). Indeed, recent studies have shown that VR can enhance the intensity of emotions as well as the sense of presence compared to non-VR stimuli (Chirico et al., 2017) and therefore better results can be achieved in ER systems (Ko et al., 2020; Yokota and Naruse, 2021) .

VR technology immerses users in three-dimensional environments in order to provoke a sense of immersion and presence. This is achieved through a combination of computer-generated objects and environments, sounds, haptics, authoring, interaction and simulation systems. In fact, Head Mounted Displays (HMD) are becoming increasingly advanced and accessible, offering more immersive VR experiences thanks to the representation of high-quality images and the use of peripherals that allow freedom of movement in the virtual environment (Parong et al., 2020).

Immersion and a sense of presence in VR are critical: users must be able to exclude the physical reality in order to embrace the digital reality offered to them. When users have higher levels of presence, they are more likely to behave in VR similarly to how they behave in physical reality, blurring the line between these two realities (Dincelli and Yayla, 2022).VR has the ability to create experiences that reliably reproduce reality or, conversely, experiences outside the laws of physics by being able to jump through space and time, endowing users with capabilities such as flying, breathing underwater, controlling objects remotely etc. (Steffen et al., 2019). This provides this technology with infinite possibilities.

In this study, an experimental setup and a protocol for the elaboration of a database of EEG recordings in which VR is used as a medium for emotion induction is described. This experimental setup is currently being used to build a sufficiently large database to be used in the development of automatic emotion recognition systems based on EEG signals.

The rest of the paper is structured as follows. Section 2 discusses the taxonomy of emotions, giving some considerations about emotion classification techniques in Section 3 . It is followed by Section 4, which outlines the methods for emotion induction while Section 5 presents some EEG databases. Section 6 describes the experimental setup, detailing the hardware and software used as well as the data collection, annotation, pre-processing and export procedures. Finally, Section 7 concludes the paper.

2 TAXONOMY OF EMOTIONS

Several models have been developed to identify and represent emotions and emotional states, being the circumplex model proposed by Russell (Russell, 1980) and developed by Russell and Feldman (Feldman Barrett and Russell, 1998) the most widely used for emotion recognition (Maithri et al., 2022). It is a two-dimensional model based on the valence and arousal dimensions, in which the emotions are distributed in a circumference in which the horizontal axis is the valence (east-west, depending on the degree of pleasure or displeasure) and the vertical is arousal (north-south, from higher to lower degree of

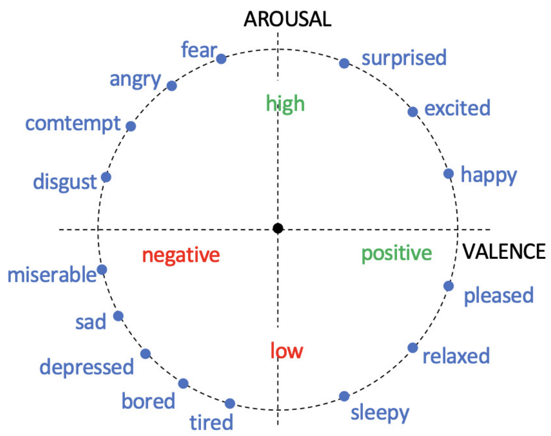


Figure 1: Circumplex model for emotion classification reproduced from (Maithri et al., 2022).

arousal), as shown in Figure 1. Thus, fear would be related to a negative emotion with a strong degree of activation, represented by an angle located in the second quadrant, much closer to 90º than to 180º. Affective states of moderate intensity can be modeled with a smaller radius in the model, with a neutral feeling being in the centre.

3 EMOTION RECOGNITION BASED ON ELECTROENCEPHALOGRAPHY

EEG-based emotion recognition methods can be classified into two broad families, methods based on traditional machine learning and methods employing deep learning (Liu et al., 2021). The recognition of a underlying emotion is, in other words, a classification task that needs an operation criteria. For this reason, there exist different feature extractions approach involved in this problems as the based on time domain features, which are focused on the waveform (Namazi et al., 2020), the based on frequency domain trying to find the spectral components of the signal (Zhou et al., 2013) or the based on time-frequency domain responding to the statistical instability of the collected EEG signals with techniques as the presented in (Gao et al., 2020). These one typically need a previous knowledge, in order to select the feature domain that fits better to the problem that wants to be solved. Instead, there is a fourth extraction approach based on the called deep domain features (Roy et al., 2019), that relays on the possibility of neuronal networks for discover and select those features that are more descriptive, loosing their physical meaning. Depending on the researching environment, the features domain selected could differ, taking into account, that the time or frequency domain features have the capability of associate the EEG recordings with biological responses. This election is independent to the database and is not unique, that is, a database can be used with any of these approaches depending on the objectives of the study.

4 METHODS FOR INDUCING EMOTIONS

Emotion induction techniques can be classified into several categories depending on the stimuli used in the experiments such as audio-visual stimuli, evoking significant emotional autobiographical memories, or introducing the subject to predefined situations with the objective of provoking a certain emotion (Barrett and Wager, 2006).

Most studies in the literature employ passive methods when the subject is limited to watching or listening to certain items selected from standardized databases. Three of these passive methods are those using verbal stimuli, music and images, for which there are a variety of databases related to various emotions.

Verbal stimulus consists of the individual reading either words or sentences written in the first person, with happy, sad or neutral emotional content. Currently, there are several lists of words classified according to dimensions such as affective valence and activation, which facilitate standardization and experimental control. The best known at international level is the Affective norms for English words ANEW (Bradley and Lang, 1999), a corpus of affective ratings for 1.034 non-contextualized words which has been expanded and adapted to many languages.

Basic emotions, such as happiness, sadness and fear can also be evoked with music (Ribeiro et al., 2019). For example, music composed in a major mode and with a fast tempo elicits happiness, whereas music composed in a minor mode and with a slow tempo elicits sadness. Some audio tracks datasets annotated with arousal and valence rating are the MTG-Jamendo (Bogdanov et al., 2019), which is composed of 18.483 audio tracks, and TROMPA-MER dataset (Gómez-Cañón et al., 2022) that contains information from 181 participants, 4.721 annotations, and 1.161 music excerpts.

The most common methods of passive emotion induction employ imagery. In the literature, there are different standardized databases, such as the International Affective Picture System (IAPS) (Bradley and Lang, 2017), Nencki Affective Picture System

(NAPS) (Marchewka et al., 2014) and its extension NAPS BE (Riegel et al., 2016), the Geneva Affective Picture Data Set (GAPED) (Dan-Glauser and Scherer, 2011) and the Open Affective Standardized Image Set (OASIS) (Kurdi et al., 2017). Currently, NAPS consists of more than 1000 color photographic images grouped into 20 sets, each with an average of 60 images classified according to the Circumplex two-dimensional model. GAPED has 730 different images rated in terms of arousal and valence within the range $[0,100]$ and OASIS contains 900 images rated in terms of arousal and valence within the range $[1,7]$.

In contrast to the passive methods described above, the induction of emotions through VR can be performed in an active way, which is more realistic and therefore led to the generation of more intense experiences. Unfortunately, there are currently no standardized databases of VR environments to our knowledge, and therefore researchers need to create their own virtual experiences or to utilize experiences developed for other purposes, usually video games.

Some researchers use image databases, such as the aforementioned IAPS in (Bekele et al., 2017) and GAPED in (Marcus, 2014), to present images in a virtual environment in a static way, for example as if they were pictures hanging on the walls of a room. Also, authors have implemented computer-generated avatars that reproduce facial expressions to evoke the emotions (Bekele et al., 2017; Gutiérrez-Maldonado et al., 2014). However, the emotional intensity evoked by these stimuli is expected to be low compared to other mechanisms more interactive.

Other authors employ immersive virtual experiences with greater dynamism. For example, in (Cebeci et al., 2019) authors induced unpleasant emotions through a terror environment and cyber-sickness through a roller coaster experience, while neutral feelings were related to a campfire environment. Also, VR games are a great source to create emotional components in the subjects, and its capability as an active method in ER systems is increasingly gaining attention among researchers in the field (Meuleman and Rudrauf, 2021; Mohammadi and Vuilleumier, 2022). Many VR games are readily available on streaming platforms such as Oculus Store for Oculus Rift (https://www.oculus.com/experiences/rift) and Steam for HTC Vive (https://store.steampowered.com/).

5 EEG SIGNALS DATASETS

An automated system for EEG-based emotion recognition needs an annotated EEG signals dataset. There are very few such datasets that are publicly available. SEED, DEAP and DREAMER are the most frequently employed, while the new BED has been recently developed.

SEED (SJTU Emotion EEG Dataset) used 15 Chinese film clips as stimuli for emotions. EEG signals were recorded from 15 participants watching those clips for 3 times (Duan et al., 2013; Zheng and Lu, 2015).

DEAP (Database for emotion analysis using physiological signals) used 40 music videos, that were shown to 32 participants while recordings were taken. Arousal, valence and dominance are provided for each recording (Koelstra et al., 2012).

DREAMER (Katsigiannis and Ramzan, 2018) consists of both EEG and electrocardiogram recordings from 23 participants. Arousal, dominance, and valence are available together with self-assessment (SA).

The BED dataset (Arnau-González et al., 2021) contains EEG recordings from 21 different individuals when using 12 different stimuli that aim to elicit concrete affective states, captured over three different recording sessions, each separated in time by one week. These stimuli include affective images from the OASIS and GAPED databases.

6 SETUP DESCRIPTION

The acquisition of EEG signals in conjunction with the induction of emotions with VR is a very complex task, both from the point of view of the interconnection of the different devices and of obtaining signals of sufficient quality due to the potential electronic noise that the VR headset can introduce in the signals recorded in the EEG helmet. In this section, the hardware and software used in the experiments is detailed as well as the main EEG signal quality problems encountered in the experiments.

6.1 EEG Signal Acquisition

For EEG signal acquisition, a solution from g.tec manufacturer was used. That consist of three hardware parts, illustrated in Figure 2 and a software connection through a Matlab script.

The electrodes in the helmet follow the international 10/20 system shown in Figure 3, so named because the electrodes are spaced between 10% and 20% of the total distance between recognizable points on the skull (frontal (F), parietal (P) occipital (O), temporal (T) and central (C)) and to the hemisphere (odd numbers for left, even number for right and Z for midline). The EEG signal is measured as the difference between the signal from the active electrode and the reference electrode. A third electrode (ground electrode) is used to average the voltage difference between the other two electrodes.

Channels AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1 and O2 were selected to be recorded. The ground electrode was allocated at Pz and the reference was taken from the right ear lobe, represented as A2. This configuration gets a distribution of information from the frontal, parietal, temporal and occipital lobes, presenting more density in the frontal lobe. The impedance between the head scalp and each electrode was reduced by deleting the air in each location by means of the use of an electro-conductive gel.

Therefore, each channel was connected to the g.GAMMAbox (tipped as 2 in Figure 2). This element handles possible artifacts such as electrode movements, 60/50Hz interferences produced by the electrical network, impedance irregularities between electrodes and skin, and background noise.

Finally, the g.USBamp-Research (tipped as 3 in Figure 2) performs the sampling task with four parallel analog to digital converters (ADC). This element presents different configurations, regulated by the oversampling factors in ADC but with a fixed bandwidth of 2,4576 MHz. After passing this component the signal recorded by the personal computer

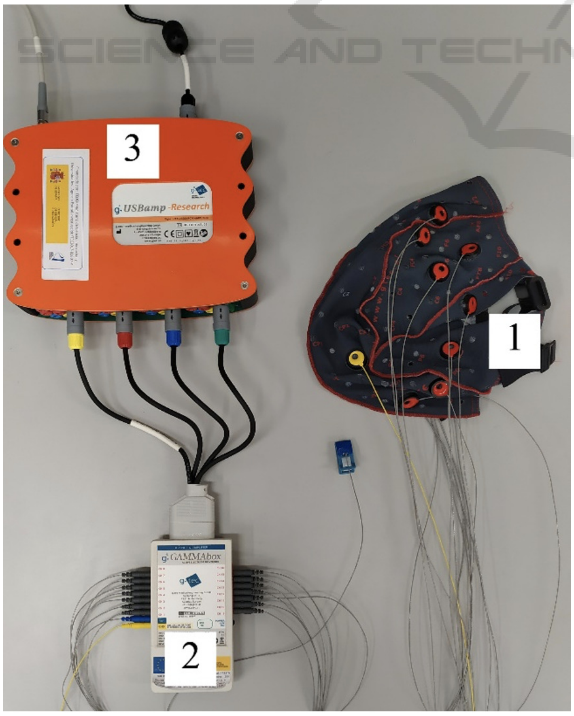


Figure 2: Hardware consisting on (1) the helmet cap, (2) the g.GAMMAbox and (3) the g.USBamp-Research.

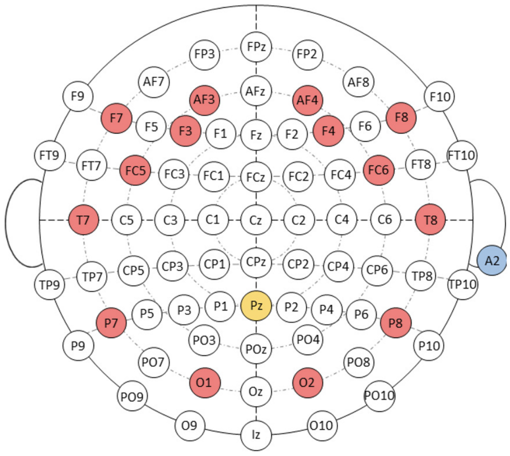


Figure 3: Helmet scheme following the 20/10 system. The channel recorded electrodes are filled in red. Ground and reference electrodes are filled in yellow and blue respectively.

(PC) via USB presented a sampling rate of 256 Hz. This sampling rate could present small instantaneous oscillations in some times, so that the time vector is also stored.

The Matlab script holds the Transmission Control Protocol (TCP) communication necessary to send the data recorded by the g.USBamp-Research to any application on the PC.

6.2 VR Environment and Headset

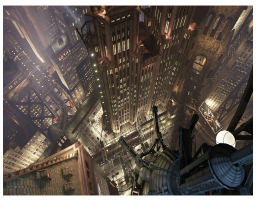
The VR environments chosen in this article have been selected to induce various emotions in a short period of time. During the experiments, the participants were invited to get into two environments. The first one was a tutorial from the Google Earth app (https://www.oculus.com/experiences/rift/1513995308673845/) with a duration of about 5 minutes. The tutorial is divided into a first introductory video of 1 minute and 33 seconds of length, and a tutorial for the use of the interactive controls of between 2 and 3.30 minutes of duration. The intention of using this tutorial is to familiarize the subjects with VR technology as well as to drive to all participants to a common state of calm and happiness in the arousal-valence plane. This first introductory stage is recorded in order to provide the researchers with an initial baseline state. The second environment projected was the Oculus Dreamdeck (https://www.oculus.com/experiences/rift/941682542593981/), a series of short experiences spanning four scenarios developed with Epic Games' Unreal Engine with 3 minutes of duration. The choice of the Dreamdeck scenario is mainly motivated by two reasons. Firstly, the recording of EEG signals can be significantly altered by the subject's movements, so it is not recommended that the subject should be able to move during the recording. Dreamdeck scenarios do not allow movement beyond head movement so subjects participating in the experiment do so seated. In this aspect, it is recommended that participants do not make sudden head movements and try to move their heads as little as possible. Secondly, the intensity with which an emotion is induced is not homogeneous over the duration of the experience. If EEG recordings are made over a long period of time, it may happen that the induced emotion is sufficiently intense only in a portion of time of the total recording, being very complicated to select these portions in the recordings once the experiment has been carried out. Accordingly, it may be preferable to have recordings of shorter duration but in which the intensity and persistence of the induced emotion is more uniform over the duration of the recording. In addition, long-term VR experiences can have undesirable side effects on subjects, such as eye fatigue, headaches and cybersickness. In this sense, the duration of the Dreamdeck scenarios, less than one minute each, is adequate and sufficient to create the database. Figure 4 shows example images of each of the scenarios.

The first scenario, called Lowpoly Forest, recreates an animal filled low polygon forest designed in a very particular artistic style. The colors, the artistic style and the sound invite the participant to a relaxed state. In this scenario VR is not used as a tool to achieve maximum realism, but the artistic style characterized by the lack of geometric details and textures together with the absence of unexpected events and shocks makes the user to feel relaxed. The second scenario puts the subject in front of a nice alien in some kind of extra-terrestrial world. The alien greets and speaks in an unknown language and keeps staring at the subject leading him or her to an excited state. In this scenario VR is used to create a sense of realism, although the fact of focusing the user in an environment that is not natural and does not belong to Earth may shock the user. At the same time, the alien is very close to the user, hence the user is attentive to what may happen, since he or she does not understand what the alien is saying and cannot know if it is a friendly environment or if it is dangerous. The third scenario places the user on a small ledge above a striking futuristic urban landscape. It is an impressive scenario that takes the user into a state of surprise. Although one might think that the height at which the user is standing might induce fear, in reality the user is aware that he or she cannot fall, only turn his or her head and inspect the environment, which is perceived by the user as a safe environment. Finally, in the last scenario, the user is confronted with a giant T-rex running towards him or her, in what looks like a museum. The T-rex roars and gets dangerously close to the user, who has nowhere to hide. It then continues on its way walking over the user, almost about to crush him, and disappears into the darkness of the corridor. In this scenario, the user is expected to be taken into a state of fear. In summary, it was expected the emotions to induce in each scenario are:

- Relaxed(Lowpoly Forest);
- Excited (Alien);
- Surprised (Futuristic City);
- Fear (T-Rex).

(a) Lowpoly Forest.

(b) Alien.



(c) Futuristic City.

(d) T-Rex.

Figure 4: Dreamdeck scenarios.

None of these scenarios allow the user to interact through the controls with the elements of the environments, which enhances the activation of arousal response in the scenarios with a possible feeling of unsafety. The VR experiences were presented to the participants using Oculus Quest 2 head-mounted display (HMD), shown in Figure 5. The VR glasses were connected to the PC by means of the Oculus Rift USB procedure. This allows real-time display on the PC of the scene observed by the user in the HMD.

6.3 iMotions Software

iMotions is a software platform capable of integrating and synchronizing tasks related to the simultaneous joint use of biometric sensors. In this work, the sensors to be integrated are the g.tec amplifier used in the acquisition of EEG signals and the Oculus Quest 2 VR glasses used in the induction of emotions This

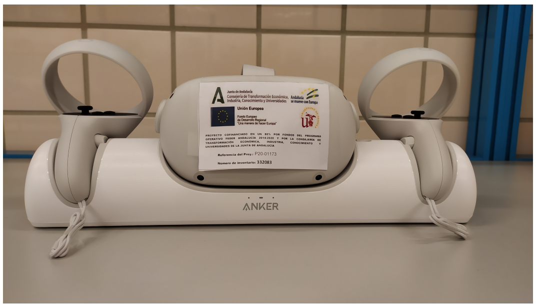


Figure 5: VR glasses and controls.

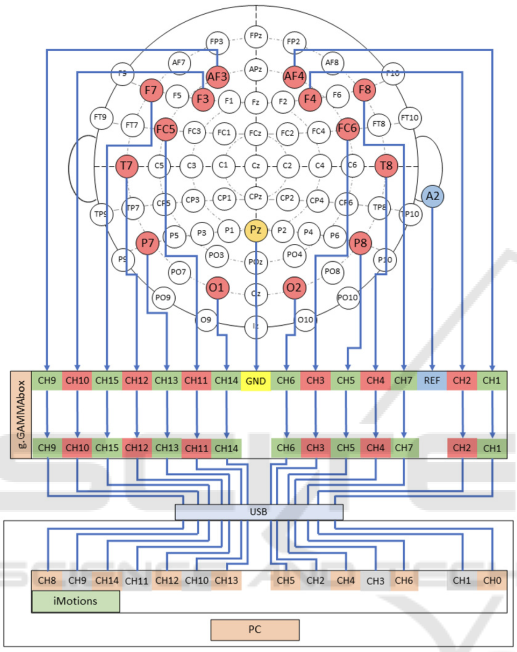


Figure 6: Channel references at the respective systems.

software not only serves as an orchestrator but also allows to check the quality of the data, to annotate them in different ways, to select epochs, to pre-process the raw data and so on.

Among all the possibilities offered by the software, the so-called screen recording is used, which allows recording everything the subject is seeing in the VR headset. This recording mode allows to specify the start and end of each type of stimulus in the time vector of the EEG signals acquired in the experiments. In this work we indicate the instants at which the Google Earth tutorial as well as each of the four Oculus Dreamdeck scenarios begin and end, these entries being available in the data exported by the iMotions software. This procedure, which is called data segmentation, is performed manually for each experiment. The connection scheme of the channels of the EEG helmet and the iMotions software is illustrated in Figure 6.

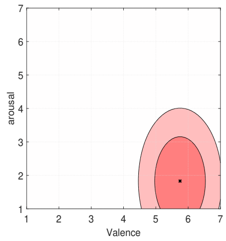
6.4 Data Collection and Annotation

At present, it has been conducted experiments with a group of 12 participants, 5 males and 7 females, with an average age of 22 years. All participants are students at the School of Engineering of the University of Seville, who have voluntarily agreed to participate in the experiments. First, the participants are informed about the experiment, its goals, safety procedures and their rights with an information sheet and through a signed consent form. After reading informative notes, the participants are asked about their familiarity with this kind of technology. After the informative stage, the subject is invited to take a sit and then, the cap is placed on his or her head. The electrodes are filled with the electroconductive gel and then the Oculus Quest 2 HMD is located and adjusted. After that, prior to conducting the experiment, the researcher carries out a pilot test to discard any problems that may encounter during data collection (the stimulus length was incorrect/non-random/non-optimal, etc.). Once it has been verified that everything is working correctly, data acquisition begins with the launch of the Google Earth's tutorial. When the tutorial finishes, the participants are asked to provide one level for arousal and one level for valence by a self-assessment mannequin (SAM) poll. Afterwards, the Oculus Dreamdeck VR experience starts. When the experience ends, the VR headset and the recording EEG helmet are removed, and the participant is provided with material for cleaning the gel on the head. Afterwards, the participants are asked to provide the arousal and valence levels for each scenario by a SAM poll. An example of a participant performing the experiment is shown in Figure 7.

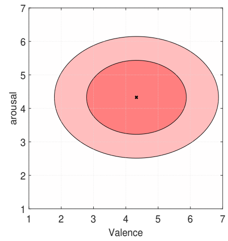
As discussed above, EEG signals are acquired continuously throughout the experiment, from the introductory experience with Google Earth to the completion of the Oculus Dreamdeck experience. This implies that in order to correctly analyze the signals it is necessary to segment the acquired data, knowing the precise instants at which each of the scenarios starts and ends. This procedure is performed by adding respondent annotations to the EEG recordings of each participant after the end of the experiment. To indicate the beginning and end of each scenario the researcher looks at the recordings to see what the participant was seeing in the VR glasses at each moment. For each Dreamdeck scenario segments of 25 consecutive seconds were selected, while for the introductory Google Earth tutorial two segments of 1 minute and 30 seconds duration were extracted.

It is very common for the same stimulus to give rise to different types of emotions in different sub-

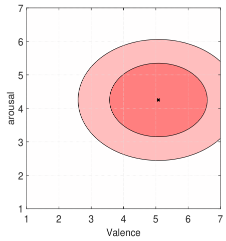
Figure 7: Example of a participant performing the experiment.



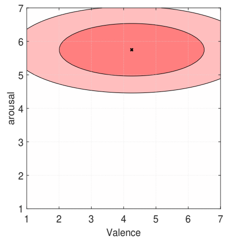
(a) Lowpoly Forest.



(b) Alien.



(c) Futuristic City.



(d) T-Rex.

Figure 8: Valence-arousal statistical representations of the Oculus Dreamdeck scenarios.

jects, and even in the same subject at different times of experimentation. Therefore, the ground truth of the induced stimulus must be provided by the participant immediately after the end of the experiment. Data annotation consists of assigning each segment an arousal and valence level provided by the participant using a SAM poll. In total, participants completed 5 SAM surveys in each experiment, one at the end of the Google Earth tutorial and 4 at the end of the full Dreamdeck experience, that is, the four Dreamdeck scenarios.

Figure 8 shows a statistical model of the annotations provided by the 12 participants in the four scenarios of Oculus Dreamdeck. In particular, the data have been fitted to a two-dimensional Gaussian distribution. Means and standard deviations of the fitted distributions are detailed in Table 1. The data from the Google Earth's tutorial is also presented.

In view of these results, it could be said that the scenes achieve approximately the emotions expected. Moreover, the Google Earth's tutorial presents the lowest standard deviation, which indicates that all participants were driven to approximately the same initial state of arousal and valence.

It should also be noted that the arousal dimension seems to increase as the experiments progress. This effect may be associated with the expectation of what the next scenario will be and the increased sense of immersion over time. Some participants also commented that in the alien, futuristic city and T-Rex scenarios they selected high values in the valence dimension because, although the scene could evoke negativity, the quality of the image made them feel positive.

Table 1: Means and standard deviations of all scenarios.

	Mean (Valence/Arousal)	Standar Deviation (Valence/Arousal)
Google Earth	6,25/2,42	0,75/1,08
Forest	5,75/1,83	0,87/1,47
Alien	4,33/4,33	1,72/1,23
Futuristic City	5,08/4,25	1,68/0,87
T-Rex	4,25/5,75	2,49/0.87

6.5 Data Pre-Processing and Export

EEG signals have a very small amplitude, on the order of microvolts, so they can be heavily contaminated with various types of internal and external artifacts and background noise. In particular, EEG recordings are prone to subject motion (breathing, blinking, head movement), power line interference and disturbances introduced by devices for emotion induction and signal recording (amplifiers, cables and VR headset) (Martinek et al., 2021). Therefore, it is very important for the researcher to monitor the quality of the signals both during the signal acquisition experiment and at the end of the experiment to decide whether or not to incorporate the records into the database.

The raw data acquired in the experiments exhibit several of these artifacts. In most of the experiments performed, the electrical potential of the EEG signals

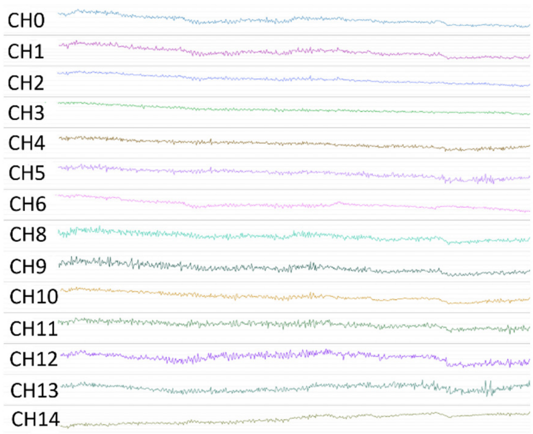
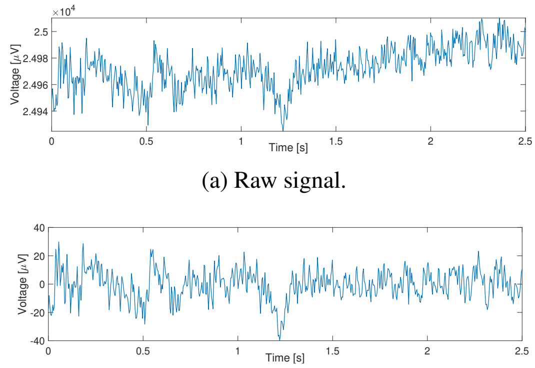


Figure 9: Example of EEG signals visualization with iMotions software of a portion of the EEG signals acquired during one of the experiments.



(a) Raw signal.

(b) Filtered signal.

Figure 10: Effect of the notch and band-pass digital filters in a portion of channel 0 (electrode AF4). The millivolts values observed in the raw signal are produced by the operation point of the amplifier.

showed a continuous decrease. Once the existence of defective electrodes was ruled out, this effect may be due to the participant's head movement during the viewing of the VR experiences worsening the connection between the electrode and the scalp, or to the lack of gel between the electrode and the skin. The best remedy for this type of disturbance is usually preventive, for example, by instructing the participants not to move their heads abruptly or move unnecessarily. However, to fully enjoy immersive experiences in VR it is generally necessary to move your head to explore the entire environment and therefore the presence of these trends are very probable. To reduce this issue the low frequencies below 0,5 Hz have been digitally filtered. Some authors use filters with cutoff frequencies of 4 Hz, however this irremediably affects the delta band ranging from 1 to 3 Hz, so it has been discarded. The raw signal has been also digitally filtered to eliminate the high frequencies above 100 Hz, and the possible presence of power line noise at 50 Hz with a notch filter. Therefore, the pre-processing of the data includes a zero phase-lag band-pass filter (Butterworth 0,5-100 Hz) and a zero phase-lag notch filter (Butterworth 50 Hz).

Figure 9 shows the iMotions data display window with a fragment of the EEG signals acquired during one of the experiments, and Figure 10 illustrates the effect of the two digital filters in a portion of EEG recording.

In case of not being able to correct these distortions and artifacts, iMotions allows you to mark time intervals in the recorded signals in which the quality of the same is not adequate for the subsequent analysis of the signals, so that only the unaffected data is exported. Currently, this process is carried out manually.

Finally, when exporting the data of the experiments, iMotions generates a .csv file for each participant. This file includes the raw sensor data provided by the g.tech amplifier, the pre-processed data provided by iMotions' signal processing algorithms as well as annotations. The voltage values are stored by columns, in microvolts, and the sample time is in milliseconds. The segments and the annotations are also stored in columns. As mentioned above, the exported data includes 25 seconds of continuous records for each VR scenario and two 1 minute and 33 seconds segments of continuous records for the Google Earth tutorial per participant. No post-processing has been done to the exported signal, leaving this aspect relegated to future improvements.

7 CONCLUSIONS

Nowadays, virtual reality is taking special importance in people's lives, not only for leisure time but also for professional development. The emotion induced by this kind of device and its impact on health has become in a dude in the last few years. This work has presented a methodology to ride experiments for creating a database of EEG signals for emotion recognition in VR environments.

The VR environments used in this experimental protocol have been selected to maximize the intensity and persistence of the emotions they are intended to induce. The first environment of the experimental protocol is the Google Earth tutorial, which has been used to provide the participant with a first contact with the VR technology without the intention of inducing any kind of emotion but to bring the subject to a neutral state. Nevertheless, it has been decided to include a substantial part of the EEG recordings belonging to this experience in the database, in order to provide the researchers with information about the initial emotional state of the subject in the experimentation. The second VR experience consists of a succession of four 3-minute scenarios called Dreamdeck. Each of these scenarios induces a different emotional state in the participant and is presented to the subjects consecutively. It is at the end of the four scenarios that the subjects complete the surveys that pertain to these four scenarios.

The database contains for each participant two segments of EEG recordings of 1 minute and 30 seconds duration corresponding to the Google Earth tutorial and four segments of EEG recordings of 25 seconds duration corresponding to each one of the Dreamdeck experiences. Currently, records from 12 different participants are available. These records show the feasibility of the proposed experimental setup for the development of a database of EEG recordings under a VR-based emotion induction protocol, although experiments with more participants are needed to create a sufficiently large database.

The combined use of EEG sensors and VR headsets is very complex and has supposed a challenge due to several reasons. First, it is necessary to configure and synchronize the data flows from the sensors and devices. This has been solved with the help of the iMotions software, which allows to capture the VR content using a screen recording stimulus along with EEG signals. Secondly, the VR glasses can interfere with the EEG helmet as well as introduce motion artifacts, both head and blink related. The artifacts found in the recorded signals are similar in appearance to the artifacts introduced by eye blinks and head movements. We did not notice any alterations in the recordings due to the electronics of the VR headsets, although we cannot completely discard this. For all these reasons, it is very important to reduce possible sources of noise in the acquired signals as well as to pay special attention to the pre-processing of the acquired signals. At present, it has not been implemented any post-processing of the signal beyond the possibilities offered by the iMotions software. In the future we want to expand the pre-processing of the signals to eliminate artifacts due to flicker as well as increase the number of EEG channels recorded and test with other virtual reality glasses.

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