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ABSTRACT
An electroencephalography (EEG)-based classification system of three levels of fear of heights is proposed. A virtual reality (VR) scenario representing a canyon was exploited to gradually expose the subjects to fear inducing stimuli with increasing intensity. An elevating platform allowed the subjects to reach three different height levels. Psychometric tools were employed to initially assess the severity of fear of heights and to assess the effectiveness of fear induction. A feasibility study was conducted on eight subjects who underwent three experimental sessions. The EEG signals were acquired through a 32-channel headset during the exposure to the eliciting VR scenario. The main EEG bands and scalp regions were explored in order to identify which are the most affected by the fear of heights. As a result, the gamma band, followed by the high-beta band, and the frontal area of the scalp resulted the most significant. The average accuracies in the within-subject case for the three-classes fear classification task, were computed. The frontal region of the scalp resulted particularly relevant and an average accuracy of (68.20 ± 11.60) % was achieved using as features the absolute powers in the five EEG bands. Considering the frontal region only, the most significant EEG bands resulted to be the high-beta and gamma bands achieving accuracies of (57.90 ± 10.10) % and of (61.30 ± 8.43) %, respectively. The Sequential Feature Selection (SFS) confirmed those results by selecting for the whole set of channels, in the 48.26 % of the cases the gamma band and in the 22.92 % the high-beta band and by achieving an average accuracy of (86.10 ± 8.29) %.

Section: RESEARCH PAPER

Keywords: Electroencephalography; brain computer interfaces; fear of heights; virtual reality

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1. INTRODUCTION

The expression fear of heights is often used as a synonym of acrophobia, a specific phobia according to the "Diagnostic and Statistical Manual of Mental Disorders" (DSM-V) [1]. A detailed definition is provided by the American Psychological Association (APA) that is, "an excessive, irrational fear of heights, resulting in the avoidance of elevations or marked distress when unable to avoid high places" [2]. Among specific phobias, the fear of heights is stated to have one of the highest lifetime prevalence, 6.8 % [1].

Fear of heights is characterized by some psychological symptoms: (i) feeling intense anxiety when thinking of or being in high places, (ii) thinking that something bad could happen in a high place, or (iii) desire to escape from the high place. Physical symptoms involve: (i) an increased heartbeat, dizziness, and daze when thinking of or being in high places, (ii) nausea, (iii) trembling, and (iv) shortness of breath. Very often people suffering from fear of heights do not seek treatment for their condition preferring to avoid the fearful situation. This can cause limitations in performing simple tasks of everyday life. Behavioural therapy is mainly used for the treatment of acrophobia. At the basis of the treatment is the exposure of the patient to the anxiogenic stimulus. The subject is slowly encouraged to enter and cope with the anxious situation. The stimulus can be imagined (imaginal modality) or delivered for real (in-vivo modality) [3]. Among the exposure approaches, systematic desensitization combines exposure with relaxation techniques [4]; graded exposure, which has been shown to be superior to the former for the treatment of acrophobia [5], involves the gradual exposition of the subject to the phobic source in a managed and controllable environment without the use of relaxation techniques [6].

For more than two decades, the literature and the clinical world have shown how exposure treatment of acrophobia can make use of Virtual Reality (VR) [7], [8]. VR is a technology that immerses subjects in a computer-generated artificial environment offering a high degree of interactivity, sense of presence and multi-sensory stimulation [9]–[11]. This has led to Virtual Reality Exposure Therapy (VRET), which shows greater efficacy than imaginal exposure [12], especially for subjects with insufficient imaginative capacity [3] and, in several cases, it is comparable to in-vivo exposure [9]. VRET offers greater control to the therapist in the administration of the expository hierarchy and allows customisation to the needs of the subject by generating adjustable stimuli [13], [14]. VRET also provides a completely safe environment with respect to the in-vivo exposure.

To date, VRET-based treatments require the operator intervention to appropriately modulate the phobic stimuli. Therefore, the adaptation cannot take place in real-time mode. In recent years, many studies have proposed therapeutic treatments involving eXtended Reality (XR) which are able to adapt to the user on the basis of real-time processing of biosignals [15]–[18]. Among the physiological signals (i.e., cerebral blood, electroculographic signals, electrocardiogram, blood volume pulse, galvanic skin response, respiration, phalanx temperature, etc), the non-invasiveness and the high time resolution represent great advantages in the use of the EEG [19]–[21]. Thus, the EEG can be successfully employed in real-time Brain Computer Interface (BCI) applications [22], [23]. Thanks to the advances in the portability and wearability of the EEG devices, VR headsets and the EEG systems are to date compatible and can be simultaneously employed.

Phobic states can cause an asymmetry in the EEG signal, that is an imbalance in amplitude or power between two sites on the scalp. Specifically, an increase in the beta power of the right hemisphere may reflect the presence of phobias [24]. A hyperactivity of the frontal cortex was also found in phobic disorders [25]. A recent study demonstrated that high levels of beta and high-beta activity in the temporal lobes (related to amygdala activation) resulted to be associated with anxiety, fear, panic, and phobia [26].

Starting from the EEG signals, fear of heights can be automatically detected by means of Machine Learning (ML) techniques.

The present study aims to identify the EEG signal processing pipeline that maximizes the accuracy of classification between 3 intensity levels (i.e., low, medium and high) of fear of heights in subjects with a different acrophobia severity. Thus, the novelty beyond the state of the art consists in focusing on the real time assessment of the intensity levels of fear experienced by a subject rather than the acrophobia severity diagnosis. This is a first step toward a BCI adaptive system for the VR-based treatment of fear of heights.

2. RELATED WORKS

In [27], the authors aimed to distinguish three groups of subjects affected by different severity of acrophobia by means of the EEG signal. The psychometric tools employed were the Acrophobia Questionnaire (AQ) and the Subjective Unit of Distress (SUD) scores. EEG data of 76 subjects were collected during the exposure to a virtual environment reproducing a wooden plank hanging at a height of about 160 m. Functional connectivity between each pair of channels was explored and complex networks named functional brain networks (FBNs) were obtained. FBNs features resulted in being able to distinguish different groups of subjects. ML algorithms and convolutional neural networks (CNNs) with FBN features as inputs were trained. The best results were achieved by using CNNs and an accuracy of (98.46 ± 0.42) % was obtained. Inter and intra-connectivity of cerebral cortex regions resulted able to identify the degree of acrophobia. In [28], the severity of acrophobia was estimated based on EEG, heart rate (HR), and galvanic skin response (GSR). The visual height intolerance questionnaire (VHIQ) was employed to preliminary assess the acrophobia intensity of the participants. 8 subjects underwent an in vivo pre-therapy exposure session, followed by a VR therapy and an in vivo evaluation procedure. Various machine and deep learning classifiers were implemented and tested in both a user-dependent and user-independent setting.

In the user-dependent setting, accuracies of 79.12 % and of 52.75 % were achieved in the 2-class (relax vs fear) and 4-class (relax, low, medium, and high) fear level classification, respectively. In the user-independent setting, accuracies of 89.50 % and of 42.50 % were achieved in the same fear level classification tasks. The EEG feature which maximized the classification accuracy resulted to be the log-normalized beta band power. In [29], EEG and ECG biomarkers of 18 subjects were real time monitored in a virtual high-altitude scenario. Statistical analysis was employed to explore the relationship between these biomarkers and the height-related stress. Perceived Stress Scale (PSS) was employed to record the subjects' self-assessment of the perceived stress. Based on a HR threshold, the sample was divided in two groups and statistically relevant differences emerged between EEG biomarkers. The absolute powers in beta and gamma bands in the occipital region were found to be associated with height-related stress. The following correlation with the PSS score were found: (i) the increase in the frontal beta power ($\varrho = 0.50$), (ii) the increase in the parietal beta and gamma powers ($\varrho = 0.56$ and $\varrho = 0.71$), (iii) the increase in the temporal beta and gamma powers ($\varrho = 0.70$ and $\varrho = 0.60$), (iii) the increase in the occipital beta and gamma powers ($\varrho = 0.53$ and $\varrho = 0.56$).

3. EXPERIMENTAL VALIDATION

In this section, the participants, the psychometric tools, the hardware, the software, and the protocol exploited for the experimental validation of the proposed study are presented.

3.1. Participants

Nine healthy subjects (age 22.63 ± 4.00; 3 males and 6 females) participated in the experiment. They were naive to the task of emotion-related visual stimulation. All participants gave prior written informed consent to participate.

3.2. Psychometric tools

The AQ [30] and the SUD scores were used for an initial screening of the sample to evaluate the severity of fear of heights. For each subject, the AQ self-report scale allows to assess the anxiety and avoidance levels associated with 20 height-relevant situations. The AQ is made of 20 items for each subscale (i.e., anxiety and avoidance).

The SUD [31] was used to monitor the fear level changes during the ongoing exposure session. It is a visual analogue scale commonly used to measure self-reported habituation of anxiety, agitation, stress or other painful feelings during the exposure therapy. Current levels of anxiety are usually rated on a Likert scale from 0 (no distress) to 100 (extreme distress). In the present study, a Likert scale from 0 to 10 was exploited. In the exposure therapy, the SUD is mainly used to develop fear hierarchies and arrange fear-provoking stimuli by order of severity. SUD ratings are generally also used to assess the initial fear level of the subjects.

Subjects simultaneously reporting AQ scores > 20 or < 6 on the anxiety and avoidance scales, respectively, and a SUD score < 2, were considered not to suffer from fear of heights. Only 1 subject belongs to this category and was excluded from the experiments. Thus, the EEG data of eight subjects were considered for further analysis.

3.3. Hardware

EEG signals were recorded through the ultra-light weight, wearable LiveAmp amplifier from Brain Products [32] (Figure 1). The system is provided with 32 gel-based active electrodes placed following the 10/20 International Positioning System.

The LiveAmp is equipped with a 24-bit analog-to-digital converter (measurement range ± 341.6 mV, resolution 40.7 nV - LSB). The EEG signals are acquired at a sampling rate of 500 Sa/s. The system is wireless and is also provided with a memory card to store the data internally in order to allow greater mobility. The rechargeable battery allows up to 4 hours recording. The BrainVision Recorder software allows to check the contact impedance between the electrodes and the scalp and the real-time visualization of the EEG data.

The Meta Quest 2 [33], produced by Meta Platforms (Figure 2) is the headset employed for the VR exposure. The Quest 2 runs an Android-based operating system and can be used both as a standalone device and with the VR software running on a desktop computer. The headset is provided with a fast-switch LCD display with a per-eye resolution of 1832 1920, and refresh rates of 60, 72, 90 Hz are supported. The 3D positional audio is built directly into the headset and a data storage of 128 GB or 256 GB is allowed. With a motion tracker with 6 degrees of freedom (DOF), the headset is able to track the movements of the head and the body, thus allowing the user a VR experience with realistic precision.

Figure 1. Brain Vision LiveAmp and actiCap.

Figure 2. Meta Quest 2.

3.4. Software

The AKRON application, developed by IDEGO [34], is a VR app designed for the treatment of fear of heights. The app allows to gradually expose the user to fearful situations by increasing the eliciting power of the stimulus. The displayed landscape is a canyon in a rocky desert, where the user can find a river and barren nature, see Figure 3.

A wooden lift and a platform allow the user to climb, starting from the ground level and reaching three increasing height levels, namely 15 m, 30 m, and 45 m. On each side, the lift is provided with protective barriers to let the user feel safe during the platform raising. Frontal barriers are not present when the platform reaches the desired level in order to leave the user in greater eye contact with the sensation of empty space. The app was developed on the Android platform using the Unity game engine (version 2019.4.16), the C# as a programming language, the OpenGLES3 graphics library, and an IL2CPP-type backend configuration. The app has been optimized through an ASTC compression system to use it on low-end virtual reality viewers such as the Meta Quest 2. A 72 Hz refresh rate was set. The 6 DOF allows the user to look around.

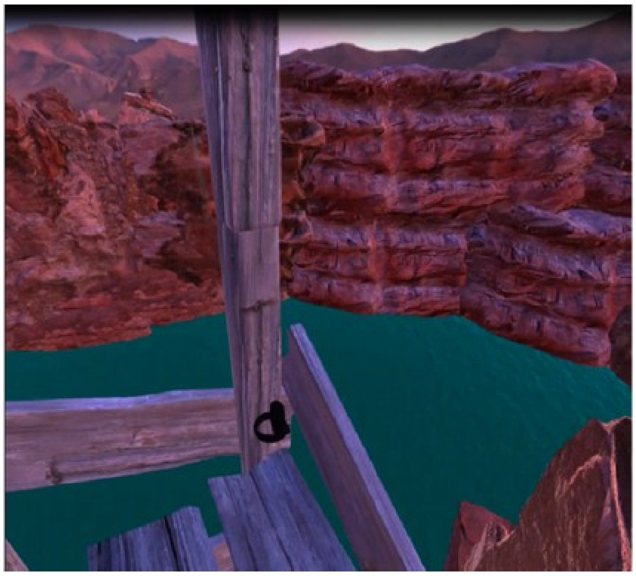

Figure 3. Displayed landscape.

Figure 4. EEG Acquisition.

3.5. Protocol

The experiments were performed at the Institute of Neural Engineering (BCI Lab) at the Graz University of Technology. For each subject, after a preparation phase, the three sessions were carried out on the same day. During the preparation phase, participants were carefully instructed on the purpose of the experiment. The researchers mounted the EEG cap on the participants head and the electrodes were filled with conductive gel. Electrodes impedance was kept under 25 kΩ and the quality of the EEG signal was visually inspected. After EEG configuration, participants were asked to wear the VR headset and the EEG signals were again visually inspected to assure no perturbations occurred (Figure 4).

Each session consisted of the same three runs. The subject is required to stand on an elevating platform in a VR environment reproducing a canyon. For each run, a higher height level is reached. Before the first run, the subject stands at the ground level to become familiar with the environment and to allow the baseline signals acquisition.

Each run starts with a visual 5 s countdown followed by the platform raising. Once reached the desired level, the subject is asked to keep that position for 90 s. At the end of the run, a message informs the subject the relax phase is starting and they are teleported at the ground level. The participant is then asked to rate the level of discomfort on a scale from 1 to 10, and the relax phase continues for other 60 s. The three sessions last about 45 min. In Figure 5, the overall experimental procedure is reported.

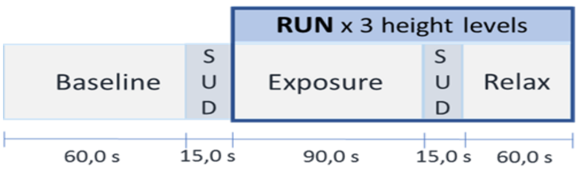

Figure 5. Framework of one experimental session. Following the baseline and the exposure phases, the subjective unit of distress (SUD) is administered.

4. DATA ANALYSIS

4.1. Preprocessing

The raw EEG data were pre-processed using Matlab v. R2022a. A zero-phase notch IIR filter was applied in order to filter out the 50 Hz power line noise. A zero-phase digital filtering was performed with a 4th order Butterworth band pass IIR filter, with cut-off frequencies between 4 and 45 Hz in order to extract the EEG frequency bands of interest. Both for the notch and the bandpass filters, the zero-phase digital filtering was achieved by using the filtfilt() Matlab function. Artifact Subspace Reconstruction (ASR) and Independent Component Analysis (ICA) [35] were employed to correct the EEG signal from artifacts through the EEGLAB Matlab toolbox version 2019 [36]. The baseline correction was then applied to the EEG signal. Next, signals were segmented into 1 s time windows with 50 % overlap between adjacent segments.

4.2. Feature extraction, selection and classification

The Fast Fourier Transform (FFT) with zero-padding was then applied to the EEG signals. The Matlab function fft() with a number of points twice the original length of the signal was exploited. The absolute powers were computed in the following frequency bands: theta (4 to 7) Hz, alpha (8 to 13) Hz, low-beta (14 to 20) Hz, high-beta (21 to 29) Hz, and gamma (30 to 45) Hz. For each frequency band, the absolute powers of channels belonging to the same brain region were averaged according to the subsequent articulation:

- frontal: FP1, FP2, F3, F4, F7, F8, FC5, FC6, FC1, FC2, Fz
- central: C3, C4, CP5, CP6, CP1, CP2, Cz
- parietal: P3, P4, P7, P8, Pz
- temporal: T7, T8, TP9, TP10, FT9, FT10
- occipital: O1, O2, Oz.

The Forward Sequential Feature Selector (SFS) algorithm was used to reduce the original dimensional feature space. The SFS belongs to the wrapper methods [37]. For a given classifier, the SFS adds or removes features to form a new feature subset. At each stage, the best feature to add or remove based on the cross-validation score is identified. The algorithm returned the most significant frequency band for each channel, by reducing the total number of features from 160 to 32.

The k-Nearest Neighbors (k-NN), Random Forests (RFs), Naïve Bayes (NB), and Support Vector Machines (SVMs) were the employed classifiers.

The goal was to classify three intensity levels (i.e., low, medium, and high) of fear of heights. For each classifier, a 5-fold stratified Cross-Validation was employed in a within-subject setting returning a mean classification accuracy for the subject. During the 5 iterations, the test fold was composed of data from randomly selected runs of the 3 sessions. The remaining data (80 %) were used for the training phase. Then, the overall mean was calculated, and the standard deviation was computed on the eight subjects considering N-1 degrees of freedom.

5. RESULTS

The metric used to evaluate the performance of the models is the accuracy that formally refers to the number of correct predictions over the total predictions. Three different experiments were carried out in order to find the most significant scalp area, the most significant EEG frequency band, and the most significant frequency band per channel.

As reported in Table 1, the highest mean classification accuracy was obtained over frontal regions.

Table 1. Within-subject classification accuracy (mean and standard deviation on all the subjects) in % of fear of heights on a 3-level intensity scale. For each scalp region, the absolute powers of the 5 EEG bands were used as input features.

Brain Region	Classifier			
	kNN	NB	RF	SVM
Frontal	53.00 ± 9.86	47.10 ± 7.15	**68.20 ± 11.60**	63.40 ± 12.80
Central	42.80 ± 4.38	43.80 ± 7.85	51.80 ± 7.98	51.70 ± 8.71
Parietal	45.10 ± 7.55	45.50 ± 4.64	53.30 ± 7.95	52.30 ± 8.27
Temporal	56.00 ± 12.20	51.70 ± 8.80	66.90 ± 11.40	62.10 ± 12.50
Occipital	52.80 ± 12.20	43.60 ± 6.27	57.70 ± 15.50	57.70 ± 15.90

Table 2. Within-subject classification accuracy (mean and standard deviation for each subject) in % of fear of heights on a 3-level intensity scale. For each scalp region, the absolute powers of the 5 EEG bands were used as input features.

Patient ID	Classification Accuracy
#1	76.20 ± 1.40
#2	57.40 ± 3.19
#3	71.70 ± 3.12
#4	53.20 ± 4.84
#5	70.80 ± 2.98
#6	62.80 ± 3.24
#7	64.00 ± 1.48
#8	89.80 ± 1.74
Overall Mean	68.20 ± 11.60

In Table 2, the classification accuracies of each subject are shown when the signals acquired over the frontal regions are input to the RF classifier. The achieved results agree with previous findings from the scientific literature: frontal area emerged to be able to distinguish among degrees of acrophobia [27].

In Table 3, classification accuracies at varying the frequency bands are reported, considering the only frontal region. The most significant EEG bands resulted to be the gamma and high-beta bands. Gamma and beta waves were observed to have a strong correlation with the brain response to high- altitude exposure [29].

These results were confirmed by the SFS when asked to select for each channel the frequency bands maximizing the accuracy. As a result, the gamma band and the high-beta band were selected in 48.26 % and in 22.92 % of channels. In Table 4, the performance of classifiers is compared when the SFS algorithm is applied to select the most informative frequency bands and when all the frequency bands are considered. A feature selection process conducted on the EEG data of each single subject allows to achieve a better performance. However, the choice of custom features would require a preliminary calibration of the system for each different subject. To pursue the goal of generalization, the gamma and high beta in the frontal area of the scalp appear to be the most robust features.

6. CONCLUSION AND FUTURE WORKS

An EEG-based detection system of three intensity levels of fear of heights was proposed. A VR scenario reproducing a canyon allowed to gradually expose the subjects to fear eliciting stimuli. By means of an elevating platform, the subjects reached three different height levels. The AQ and the SUD scores were employed to assess the severity of fear of heights of the experimental sample. The EEG signals of eight subjects were acquired through a 32-channel headset during the exposure to the VR scenario. A detailed analysis was conducted in order to highlight the scalp regions and the EEG bands mostly affected by fear of heights. The average accuracy in the within-subject case for the three-classes fear classification task, was computed. The absolute powers in the five EEG bands extracted from the frontal region of the scalp allowed to achieve average accuracies of (68.20 ± 11.60) %. Considering the only frontal, accuracies of (57.90 ± 10.10) % and of (61.30 ± 8.43) % were achieved in the high-beta and gamma bands, respectively. The SFS confirmed those results by selecting for the whole set of channels, in the 48.26 % the gamma band and in the 22.92 % the high-beta band and achieving an average accuracy of 86.10 ± 8.29. In future works the sample size will be enlarged and further EEG features will be tested to improve the generalizability of the results.

Table 3. Within-subject classification accuracy (mean and standard deviation) in % of fear of heights on a 3-level intensity scale. For the frontal region, the absolute powers of the 5 EEG bands were separately used as input features. The two bands maximizing the accuracy for all the classifiers are highlighted in grey.

Frequency Band	Classifier			
	kNN	NB	RF	SVM
Theta	39.30 ± 4.76	37.90 ± 3.26	41.60 ± 6.52	39.40 ± 7.66
Alpha	41.20 ± 4.52	38.90 ± 6.45	42.70 ± 5.92	43.30 ± 6.43
Low-beta	50.80 ± 11.00	45.70 ± 8.70	52.10 ± 10.80	52.00 ± 11.40
High-beta	53.60 ± 13.40	49.70 ± 9.16	57.40 ± 12.50	57.90 ± 10.40
Gamma	57.80 ± 9.37	46.60 ± 6.90	61.20 ± 9.76	61.30 ± 8.43

Table 4. Within-subject classification accuracy (mean and standard deviation) in % of fear of heights on a 3-level intensity scale. The absolute powers of the 5 EEG bands were used as input features. Results with- and without feature selection are reported.

SFS	Classifier			
	kNN	NB	RF	SVM
With-	78.60 ± 8.50	55.40 ± 8.29	**86.10 ± 8.29**	85.70 ± 9.12
Without-	59.50 ± 12.50	52.30 ± 7.09	82.00 ± 11.60	76.70 ± 14.00

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