Active touch classification using EEG signals

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Abstract*—Touch is a fundamental aspect of human interaction with the surrounding environment. It affects individuals' development in different manners and figures prominently in everyday operations such as the sense of presence, object recognition, performing actions, non-verbal communication and emotional state. In recent years there has been a growth of interest in researching the electrophysiological activity of the brain originating from haptic stimulation. In the present preliminary experiment, we performed a classification process of extracted EEG features acquired from four healthy participants' EEG data when they actively touched different natural textures. Each participant was asked to use their fingertips and calmly rub for one minute, each of the three different textured materials (smooth, rough and water surface). EEG recordings were acquired and processed. Next, time and frequency-based features were extracted and used as input to four classifiers to correctly identify each different texture. The results obtained show a classification performance of 63% with C4.5 algorithm and 76% with Random Forests and 10-fold cross-validation.

***Keywords*——Classification; Electroencephalogram; EEG; Machine Learning; Haptic; Active touch**

I. INTRODUCTION

The sense of touch is one of our basic mechanisms for perceiving and exploring the world around us. It starts developing in the infancy stages [1] and accompanies us forthe rest of our lives playing an effortless but major role. Loss of the sense of touch would lead to losing the feelings of pain and temperature, losing the sense of presence and much more [2].

Exploring our surroundings requires a kind of movement/interaction with an object's surface using our fingertips due to their high sensitivity. Starting from the mechanical stimulation of the skin, different types of mechanoreceptors convert energy that leads into the production of a nerve signal that travels through the spinal cord and thalamus, to the brain and more specifically the primary somatosensory cortex [3]. Once the signal has reached the brain coming from the different nerve pathways, signals travel to the post-central gyrus (S1, S2) and other higher-order areas (or somatosensory areas). The processing of that signal in the brain combined with the cutaneous, kinesthetic and thermal information is referred to as haptic perception.

Haptic perception is a subjective experience [4], [5] and apart from its apparent importance in drawing information for daily tasks regarding object manipulation and performing actions, it impacts the emotional and social human cognition [6], [7]. Geometric and physical properties of the surfaces touched can be perceived including roughness, texture type, hardness or temperature [8]. The form of touch can be either active, thus including voluntary movement or passive (tactile). Perceptual differences between each form are not yet fully understood and numerous articles substantiate the different approaches [9], [10]. Visual, auditory and memory aspects also contribute to haptic perception thus forming a multimodal process [4].

Decoding haptic modality is of great significance due to its various applications in the medical, technological and industrial fields along with the social, cognitive and affective parts of human activity. Such applications can be limb rehabilitation, interface and application design or interactive media. Methods of neuroimaging such as functional Magnetic Resonance Imaging (fMRI) and Electroencephalogram (EEG) have made it possible to observe the response of the brain cortex to touch stimuli in a non-invasive way. EEG particularly, offers a low cost high temporal solution that can be utilized under different experimental scenarios due to its portability and ease of use. Research interest in using EEG to study haptic sensation has been increasing over the last few years. Most studies examine the activity of basic brain frequency bands or explore the function of the somatosensory pathways and the neural responses related to haptic input using analysis techniques such as PSD, ERP, SEP and SSSEP [7], [11]. Recent implementations of EEG analysis incorporate machine learning techniques attempting to algorithmically classify different brain states under haptic stimuli. These studies investigate discriminative touch and touch imagery [12] [13], roughness recognition classification [10], [14], [15] and tactile pleasantness in response to different textures or type of touch [16], [17], [6].

The objective of this preliminary study is to discriminate between different natural material textures during active touch using EEG and classify them with different machine learning algorithms. Despite the renewed research interest in capitalizing on machine learning algorithms and EEG [18] to the best of our knowledge, only a few studies have focused on examining the haptic modality and even fewer that employ multiple algorithms in their approach. In Section II adescription of the experimental protocol is laid out along with the EEG signal acquisition and data processing. Next, Section III reports the classification accuracy results and discussion. Finally, Section IV includes the conclusion and future work.

II. Methodology and Materials

In the proposed approach, the EEG signals were acquired from the Emotiv EPOC Flex wearable device and features re-extracted from the OpenViBE BCI software [19]. A flowchart of the proposed classification process is depicted in Figure 1.

A. Participants

Four healthy participants, with no history of neurological or psychiatric disorders, voluntarily took part in the experiment. Two of them were male and two females, all right-handed and aged between 25-27. The study was under the supervision of the Department of Informatics and Telecommunications of the University of Ioannina. All participants were informed about the procedure and were asked to read and sign a written consent form before the experiment, after ensuring that there was no question nor hesitation regarding the experimental protocol or data privacy.

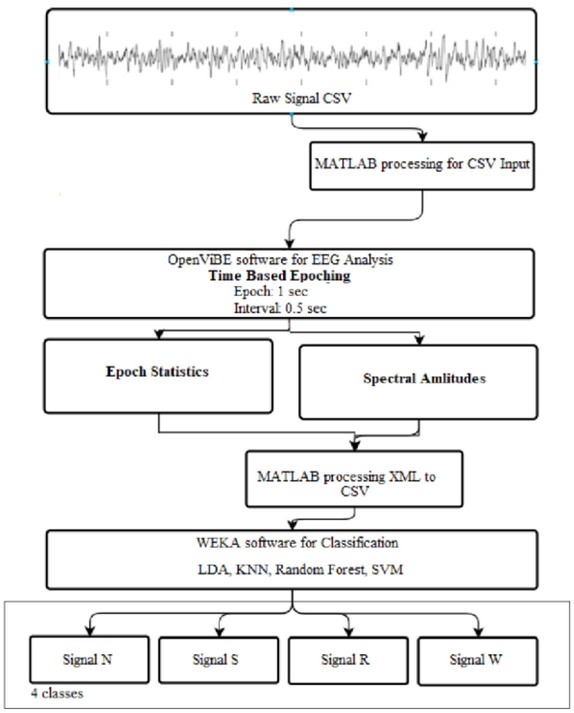

Fig. 1. Flowchart of the classification process followed. Signal N correspond to the resting state whereas Signals S, R and W correspond to smooth, rough, and water material textures respectively.

B. Experimental Procedure

Experiments were held in a controlled environment. Participants were asked to comfortably be seated in a chair within a clinical environment. Initially, a researcher explained the procedure to the participants. Before the experiments, participants got familiar with the device and were instructed to remain calm and relaxed during the procedure. Then, their dominant hand (i.e. right hand) was positioned in a fixed place on an ergonomic arm support. The different texture materials were placed in front of them on a table so that they could be seen. Subsequently, they were asked to relax and remain calm for one minute before any task begins. Next, participants were asked to use the fingertips of their right hand to softly rub each texture for one minute, in a circular, clockwise manner, without applying pressure on any material. Also, they were asked not to actively think about the type of texture they were interacting with. The procedure was repeated three times for each participant and sufficient resting time was given in between changing materials and repetitions. The protocol in brief steps:

- A 1-minute resting-state recording
- A 1-minute recording during active texture rubbing
- A 2-minute short break with no stimuli

Then, the protocol was repeated for two more trials. The procedure was constantly supervised by an experienced researcher of the team.

C. Materials

Three natural material textures were used in this preliminary experiment. Two with different levels of roughness (smooth and rough) and room temperature water. All materials were placed at the same height level relative to each participants' hand so that any different postures and movements of the hand would be minimized while touching the surfaces.

D. Data acquisition

The proposed Brain-Computer Interface (BCI) system utilizes the EPOC Flex head cap system. EPOC Flex is a wearable EEG recording device equipped with a rechargeable lithium battery and 32 gel Ag/AgCl sensors for recording brain signals. Each sensor is placed at certain locations in the scalp (F3, F4, FC3, FC4, C1, C3, C5, CZ, C2, C4, C6, CP1, CPZ and CP2 etc.), according to the 10-20 International System with a frequency response of 0.16 – 43 Hz. The visualization of the recordings along with the quality of the connectivity was performed with Emotiv software (EmotivBCI) in real-time.

In the proposed experimental protocol, three sessions were held to capture EEG data, ensuring the quality of the recordings. The data were digitized at a sampling rate of 1024 Hz, downsampled to 128 Hz and transmitted to a PC using a wireless connection. The quality of each sensor's connection and the humidity of the pads were regularly checked through the EmotivBCI software to ensure high conductivity and quality of the recording.

E. EEG data processing and feature extraction

The OpenViBE BCI [19] software is used for processing the recorded signals and has been previously used successfully[20]. OpenVibe is an open-source software platform for real-time BCI applications and it is freely available from the French Inria Institute. It includes a design tool for creating and running applications and many more features that are already predefined for use. OpenVibe can be used to obtain, filter, process and visualize signals from the human brain. It is an easy-to-use environment and includes a Scenario Designer canvas for script development incorporating many functions to use and an Acquisition Server that provides the drivers for the direct communication between the EEG device and the software.

The platform use is twofold: a) for offline applications with EEG laboratory prerecorded data and b) for online application with EEG signals obtained in real-time. Regarding the quantitative EEG information extracted from each subject, the .csv file retrieved from the EEG headset was made compatible with the software through a script developed in MATLAB and then was segmented into epochs of 1 second with 0.5 seconds interval offset. After that, 11 different characteristics were calculated, wherein six of them are statistical features. These statistical features are computed through the "Univariate Statistics" box of the OpenVibe BCI software. The “Spectral Analysis” box performs Fast Fourier Transform to analyze the EEG epochs and extract the spectral features. Time and frequency properties are extracted for each epoch creating the classification dataset. More specifically, as far as the spectral components are concerned the spectrum amplitude for the five frequency bands of interest is extracted:

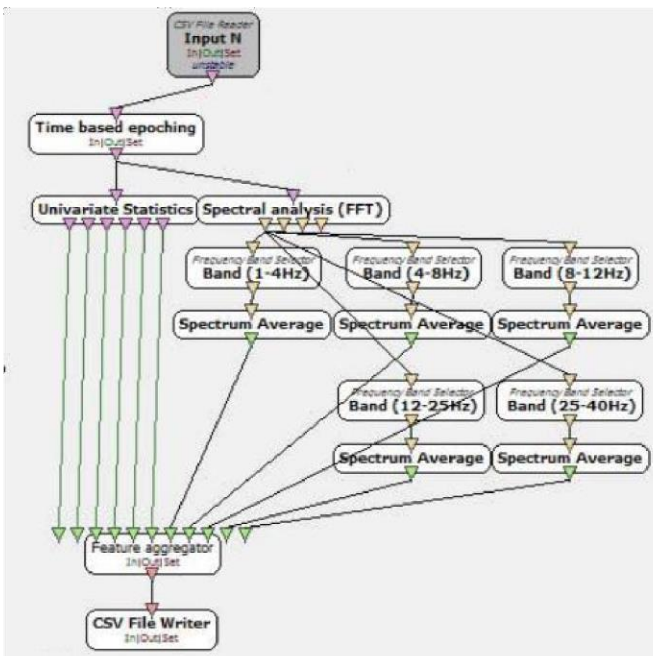

Fig.2 The scenario for epoching, data processing and feature extraction within OpenViBE BCI platform.

- Alpha waves frequency: 8-12 Hz.
- Beta waves frequency: 12-25 Hz.
- Theta waves frequency: 4-8 Hz.
- Delta waves frequency 1-4 Hz
- Gamma waves frequency 25-40 Hz

Regarding the Time-Based Features, for each epoch, the Mean Value, Variance, Range, Median, IQR and 30% Percentiles are extracted.

Finally, the "Feature Aggregator" box of the software forms an array with all the extracted EEG attributes to train several classifiers. Specifically, the columns of the feature table contain the received characteristics and the rows represent the instances of these characteristics. Thus, for each epoch, a set of11 spectral and time-based features is calculated. All the EEG features are exported to a .csv file. In Figure 1, the OpenViBE scenario is presented and Table I presents, in brief, the extracted EEG features.

F. *Classification*

The validation of the proposed system is performed on 4 classification algorithms, specifically Linear Discriminant Analysis (LDA), Support Vector Machines, K-Nearest Neighbor (KNN) and Random Forests. The Weka [20] platform was employed for the classification purposes of the study. Again, the exported .csv file containing all the features for each EEG signal was made compatible with Weka througha Matlab script. Four different algorithms were hired to solve a 4-class problem aiming to discriminate between the different natural material textures (resting state, smooth, roughand water).

1) *Linear Discriminant analysis*

Linear Discriminant Analysis (LDA) is used in statistics, pattern recognition and machine learning to find a linear combination of characteristics that will separate the instances. This linear combination can be used as a linear classifier. The LDA method performs well when the measurements made in independent variables for each observation are continuous variables. The representation of the LDA is a straight line, while the statistical properties are calculated from the data andlinked to the LDA equation to make the necessary predictions [22].

TABLE I. EXTRACTED EEG FEATURES

	Feature Details	
	Feature type	***Feature Description***
1	Time-Based Features	Mean value of EEG signal epoch
2		Variance of EEG signal epoch
3		Range of EEG signal epoch
4		Median value of EEG signal epoch
5		Inter- Quantile-Range
6		Percentiles (30%)
7	Spectral Features	Spectrum Amplitude for Band (1-4 Hz)
8		Spectrum Amplitude for Band (4-8 Hz)
9		Spectrum Amplitude for Band (8-12 Hz)
10		Spectrum Amplitude for Band (12-25 Hz)
11		Spectrum Amplitude for Band (25-40 Hz)

2) *Support Vector Machines*

Support Vector Machines (SVM) have widely been used in biomedical applications and particularly in EEG analysis. The basic idea underlying the SVM classifier is to map the features into a high-dimension feature space and locate an optimal separating hyperplane to maximize the distance between the margin and the data lying on the margin (i.e. support vectors) while maintaining a low classification error [23].

3) k- Nearest Neighbor

kNN is one of the simplest machine learning supervised algorithms. In this non-parametric method, the classification of an instance to the most relative class is based on the vote of its k nearest neighbors, with k being a positive integer. This simple technique is widely used in biomedical applications [22].

4) Random Forests

Random Forests proposed by L. Breiman [24] is an ensemble learning method that is widely used in EEG-based classification problems. The method is an extension to the bagging idea and combines decorrelated decision trees, aiming to reduce the generalization error and improve the classification accuracy. In this classifier, a group of features is selected to train and test each individual decision tree and theneach tree is responsible for its classification while in the end, the trees vote for the most popular class.

Overall, for each algorithm 10-fold-cross-validation testing method was used. Weka's implementations of both the algorithms and the testing method were used. Two different data sets were used for the classification. First, all the spectral and time features were included in the dataset and secondly, only the frequency features were included.

III. Results And Discussion

Table II presents the accuracy levels results achieved by each classification algorithm when all the temporal and spectral features are included, compared to only using temporalfeatures.

TABLE II. RESULTS IN TERMS OF CLASSIFICATION ACCURACY FOR EACH CLASSIFICATION ALGORITHM FOR THE 4-CLASS PROBLEM RESTING-STATE- SMOOTH-ROUGH-WATER

Algorithm	**Accuracy**	
	Temporal and Spectral Features	***Spectral features***
LDA	71.4931	65.9722
Random Forests	76.7014	72.5347
KNN	64.2014	56.2500
SVM	75.3472	63.1944

Results showed accuracy levels of the classification experiments ranging between 64% to 76%, indicating that the EEG signal characteristics can indeed be used to identify the diverse brain states when different haptic stimuli are applied. This is supported by the fact that the performance level of the classification algorithms considerably exceeds the level of opportunity for each class (25%). Additionally, it is important to notice the fact that higher accuracy is achieved in all classification algorithms when all features are employed in contrast to using frequency features only. Suggesting that time features like mean value and standard variation incorporate information that should be utilized. Moreover, the nature of the classification problem appears to have linear characteristics since both LDA and linear kernel SVM achieve much higher accuracy levels, similar to Random Forests. On the contrary, kNN algorithm achieves the lowest accuracy levels, implying that the problem is not favored by the localization of samples in the feature space.

IV. Conclusion and Future Work

In the present study, EEG data acquired from multiple participants were used to assess the brain activity caused by haptic stimulus. Participants were exposed to four different types of stimuli, one of which was neutral and therefore no haptic nor any other kind of sensory stimuli was present (visual, auditory etc). EEG recordings were collected with the Emotiv Flex device using multiple channels (34 recordingchannels). Similar studies have been carried out in recent yearsproviding useful insight into the field of physiology and psychology of humans. Therefore, the variations in the methodology of the present study further contribute to theresearch field. The signals collected, were divided into epochs of 1 second, time and frequency features were extracted and were used in combination for creating a scenario within the OpenVibe open-source software. Finally, the signal samples were classified using four different classification algorithms (LDA, KNN, Randoms Forests, SVM) aiming to identify whether brain signals behave distinctly under different haptic stimuli.

Future work which builds on the present study concerns the field of human psychology and physiology. Indicatively, we propose leveraging immersive technology such as Virtual Reality to incorporating human emotion (pleasure/displeasure), cognitive and imagery aspects as well as, kinesthetic andtactile associations with haptic stimuli. Furthermore, improving the feature selection process by analyzing the neurophysiological activity of the brain in conjunction with increasing the participant pool could produce more accurate and generalizable results. Finally, the experimental procedure along with the recording protocol can be further optimized by leveraging existing literature.

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