Detection of Tactile Feedback on Touch-screen Devices using EEG Data

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Abstract— **Neurohaptics strive to study brain activation associated with haptic interaction (tactile and/or kinesthetic). Understanding the haptic perception and cognition has become an exciting area in the technological, medical and psychophysical research. Neurohaptics has the potential to provide quantitative (objective) evaluation of the user haptic experience by directly measuring brain activities via EEG devices. In this study, we employed a Machine Learning (ML) based classifier model, namely the Radial Based Function Support Vector Machine (RBF-SVM) to select a few relevant Electroencephalography (EEG) channels and to detect the presence of tactile feedback during interaction with touch-screen devices using EEG data. To overcome the problem of limited training data, time-shifting is proposed as a method for data augmentation in time-series neural data which increased the classification accuracy. An experimental setup comprising an active touch task on the Tanvas touch-screen device is designed to evaluate the developed model. Results demonstrated that the middle frontal cortex, namely channels AF3, AF4, and F1 produced the best recognition rate of 85±3.3% in detecting the presence of the tactile feedback. This work is a step forward towards building a quantitative evaluation of tactile experience during haptic interaction.**

I. INTRODUCTION

Neurohaptics strives to study brain activation resulting from haptic interactions. It intends to study cognitive processes associated with haptic interaction which in turn can provide a quantitative means to measure the human haptic experience. It is known that tactile sensations from the skin form a complex experience in the cerebral cortex, the most advanced part of the brain. Brain activation associated with tactile sensation involves different parts of the brain such as the somatosensory cortex, motor, parietal, frontal among others. Determining what part of the brain associates to a particular haptic experience remains largely unexplored. In the recent years, novel methodologies to explore the neurobiological bases of mind and behavior have inspired the field of haptics to study the human haptic experience [1].

Functional Magnetic Resonance Imaging (fMRI) and Electroencephalography (EEG) are well established techniques to study brain activation. They provide a quantitative measure for the participants' neural processing of perception and cognition in real-time [2]. fMRI measures brain activity by monitoring the Blood-oxygen-level-dependent (BOLD) in the whole brain as BOLD is coupled with neural activation [3]. Even though fMRI has a high spatial resolution and is capable of imaging deep brain activities such as the limbic system, it is costly and suffers from technical challenges in accommodating electronics in the experimental setup due to the extremely high magnetic field. It also has a limitation of low temporal resolution (for instance, a single frame of whole brain scanning would take two to three seconds) [4]. On the other hand, EEG is a lower cost apparatus that is capable of recording the cortical neural activation in the presence of human-machine interaction. Participants can sit and perform limited movements while recording EEG data. EEG also has a high temporal resolution, particularly useful for real-time analysis of the neural mechanisms associated with haptic interaction.

Recently, machine learning algorithms are increasingly applied in EEG studies to uncover relevant information for neural classification and neuroimaging. Machine learning algorithms are generally used to automatically make predictions or decisions by learning patterns from a provided dataset without a predefined rules or regulations. Machine learning models are formed based on a sample data to perform usually either regression or classification. In regression, a relationship is formed between an independent variable and a target variable where the target variable is a continuous numerical quantity. In classification, however, the model tries to predict a category from a predefined set of categories. Machine learning techniques have been used on physiological signals and human body scans such as EEG [5] [6], fMRI [7] [8], ECG [9] [10] and EMG [11] [12] to provide assistance in the healthcare sector and to learn more about the human body and the way it functions. Mostly, these studies aim to predict, classify or identify anomalies or impairments in test samples that were not part of the training data; for example, data from a new patient. Machine learning techniques proved useful in these diagnosis procedures.

Machine learning techniques have been also used in few neurohaptic experiments for different purposes either related to the haptic task (whether tactile or kinesthetic, passive or active) or the haptic experience itself. A study by G. Cisotto et al. investigated the possibility of classifying grasping tasks of objects with varying weights and tactile features from EEG and EMG data [13] while M. Pal et al. used EEG and pressure sensors data to classify explored wooden objects with varying shape complexity [14]. Another study by J. Kim et al. used Gaussian Nave Bayes (GNB) classifier to decode pressure locations on fingers from recorded fMRI data [15]. Machine learning based models were also used to classify EEG data to determine the degree of pleasure level in interpersonal touch perception such as soft touch, massaging and embracing [16].

In this work, we aim to use a Support Vector Machine

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model based on Radial Basis Function kernel (RBF-SVM) in identifying the most influential channels for detecting the presence or absence of tactile feedback during an active touch task interaction on a touch-screen device. Tanvas Touch device is utilized in this study to provide tactile feedback on the touch-screen. This classification method aims to provide haptic designers a quantitative method to detect the presence of tactile feedback during the interaction with an object (virtual or real). Furthermore, the proposed method can be used to aid designers distinguish which tactile features are more prominent in a specific product. The RBF-SVM model is utilized for finding few EEG channels that associate the most with the tactile feature cognition. Eventually, the trained classifier model is upgraded to perform classification task through the identified channels with an improved accuracy using voting classifier and data augmentation through time-shifting which is suitable for EEG time-series data.

The remaining of the paper is organized as follows: section II presents the proposed method including the representation of the data, feature extraction, the EEG channels selection paradigm and the classifier. In section III, the details of the neurohaptic experiment, in order to validate the proposed method, are explained. In section IV, results and discussion points are presented. Finally, section V presents a summary of the findings and provide perspectives for future work.

II. Proposed Method

In this work, we aim to: a. Find the most relevant EEG channels that carry distinctive information about the neural response of tactile stimulation b. Build a reliable classifier that is capable of distinguishing between the two haptic conditions given the data from the relevant EEG channels. Figure 1 highlights the main steps undertaken in the proposed method. Using a Machine Learning (ML) based classification technique, we demonstrate how to select EEG channels that associate the most with the presence of tactile stimulation in an active touch task. The proposed method goes as follows: After acquiring the EEG signals, the data is pre-processed and epoched such that specific time windows are extracted from the continuous EEG stream locked around the touch event. We then extract the beta band power as it is associated with the cognitive processing, awareness and sensorimotor states [17]. Irrelevant features, namely the EEG features before the touch onset, are discarded and only the EEG points right after the touch onset are considered.

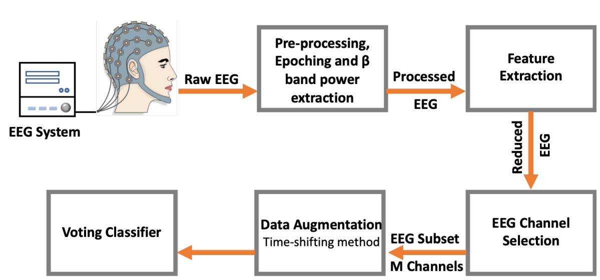

Fig. 1. An overview of the proposed methodology

The reduced EEG data is then fed to the Channel Selector in which a non-linear ML based classifier is trained to identify the most relevant EEG channels. EEG signals from the selected channels are assumed to exhibit the highest significant difference between the two haptic conditions. The models trained in the Channel Selector are used to build a non-linear voting classifier capable of differentiating between the two haptic conditions given a set of the EEG data. We use time-shifting as means of data augmentation for the sake of improving the training dataset and hence, improving the performance of the classifier.

A. Dataset

In this study, we utilize the EEG recordings produced in our previous work on active touch task [18]. Twenty-six subjects were recruited for this experiment in which each of them performed the experiment under two haptic conditions (with/without tactile feedback). Each subject had to undergo 96 trials per mode and EEG data was recorded across 58 channels on the scalp. To facilitate referring to the above parameters in the remainder of the manuscript, we list them in Table I.

TABLE I
Parameters of the Data

Parameter	Symbol	Value
Subjects	N	26
Channels	Ch	58
Modes/Condition	M	2
Trials	Tr	96
Time Indices	I	70

The 96 trials per subject per mode were averaged out locked to the touch onset; averaging EEG epochs increases the signal to noise ratio and assist the classifier to be more robust. Power spectral density (PSD) in the beta band was calculated from the time series data. In order to prepare the data such that the top performing channels are selected, data should be split in smaller matrices. Each matrix will have 52 rows representing trials (26 subjects under two modes) and 70 columns (70 features or data points per epoch); each matrix represents the data from one channel in beta band. Thus, 58 such matrices will be formed.

B. Feature Extraction

Every EEG data point is a feature by itself. We aim to extract the features (i.e: data points) that contribute in differentiating between the two haptic modes. Prior to the onset, there is no differentiating features between the modes as can be seen from the example epoch in Figure 2; the relevant EEG activity starts after t =0. Thus, epochs were truncated such that only the latter part of the epoch was considered. Figure 2 shows PSDs from the 26 subjects, channel AF3, beta band, as an example of a channel that showed a difference between the two stimulation modes from our preliminary analysis.

Thus, the number of points (features) was reduced from 70 to 35 per epoch. Another advantage of this extraction is

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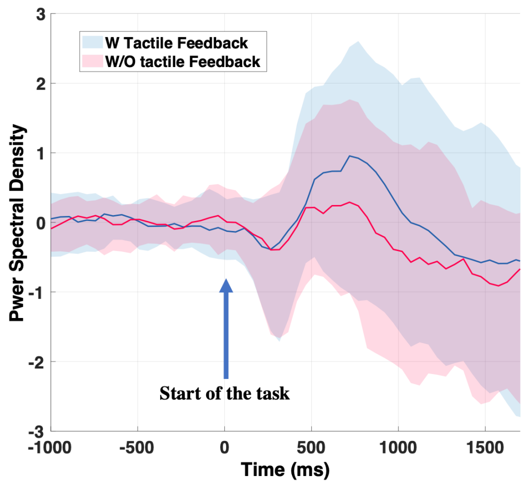


Fig. 2. PSD for 26 subjects from AF3 beta band under the two modes. Hard lines show the mean of the trials while the shaded area represents the standard deviation.

that the number of features (columns) is now less that the number of observations (rows). This ensures that we avoid over-fitting and increases the robustness of the models [19].

C. Channels Selection

As a matter of fact, EEG data is high dimensional and non-linear in nature and thus, simple classifiers such as logistic regression or classifiers with linear kernels are not adequate. Support Vector Machine (SVM) with non-linear kernels proved to perform relatively well in EEG data classification as reported in the literature [20] [21]. Here, we train a Radial Basis Function SVM model to find the relevant EEG channels. Selecting relevant channels is important due to three main reasons: (i) reducing the computational cost and time (ii) reduce over-fitting due to unnecessary or irrelevant channels (iii) reduce the setup time in future experiments [22]. Linear SVM is a discriminative classifier that is capable of classifying two or more categories by realizing an optimal line (or hyperplane in higher dimensions). If the dataset is non-linearly separable, a kernel function is used in order to map the data to another space, usually a higher dimension space, such that the data is linearly separable. Once the hyperplane is realized, the features and the hyperplane are both re-mapped to the original space. SVM algorithm tries to maximize the margin between the data points and the separating plane while minimizing the number of the mis-classified data points. The following equation describes the loss function of a linear SVM in which it is minimized during the training iterations [23]:

$$J(w,b) = C1\sum_{i=1}^{N} max(0, 1 - y_i(w^T x_i + b)) + \frac{1}{2}\left\|w^2\right\| \quad (1)$$

where J is the loss function, w and b are the hyper-plane parameters, x and y are the data points to be classified, and C1 is the regularization parameter. The first term is called Hinge loss and it controls the mis-classification while the second term controls the margin. Thanks to these two terms, SVM is known to have a very good generalization properties, being insensitive to over-fitting, and immune to the curse of dimensionality [24] [25] [26]. In this work, we used the Radial Basis Function (RBF) as a kernel mapping function for the EEG data which is given by [23]:

$$K(S1, S2) = e^{-C2\|S1-S2\|^2} \quad (2)$$

where C2 is a free parameter. An optimum C1 and C2 must be found for an RBF-SVM model. There are two hyper-parameters to be optimized for every SVM model: C1 and C2. C1 is a regularization parameter that controls the cost associated with mis-classification; the higher the C1, the more is the penalty for the mis-classified points. C2 on the other hand, is the free parameter from the RBF kernel used to handle non-linear classification. Higher values of C2 allow for highly non-linear decision boundaries which can, after some point, convert into decision islands surrounding data points leading to over-fitting. We created four SVM models, each corresponds to a specific cortical region: ipsilateral-parietal, contralateral-parietal, middle-parietal and middle-frontal regions. This selection is based on the findings of our previous study [18]. Hyper-parameters for each model are optimized to provide its best possible accuracy. The cortical region exhibiting the highest classification will be first identified; best performing channels within the identified region are selected.

D. Classifier

We aimed to improve the classification accuracy of the best performing model (brain region) after being selected. This was done by identifying the best performing channels within the selected region that provide the highest relative classification accuracy. Grouping these channels in a voting classifier scheme is expected to increase the classification accuracy. Voting classifier is not a classifier per se, but it is a wrapper for a set of models that combines their outcome through majority voting. The voting classifier model is trained by implementing a stratified 10-fold cross validator in order to preserve the percentage of the samples for each class in both, training and testing. This is to guarantee a proper coverage of both modes; this is especially important when the data size is limited. Additionally, it is reported that stratified k-fold cross validation is generally a better schemer when compared to the regular cross-validation [27]. To further increase the accuracy of the voting classifier, we propose using time-shifting as an augmentation technique on the training data which we found suitable for EEG data. Other studies reported using window slicing [28] or window wrapping [29] as augmentation techniques for EEG data [30]. Figure 3 below explains the implementation of the proposed scheme of preparing and processing the EEG data to achieve a boosted classification accuracy.

III. Experimental Study

The neurohaptic study aimed to investigate the neural response of tactile stimulation through a tablet device. A

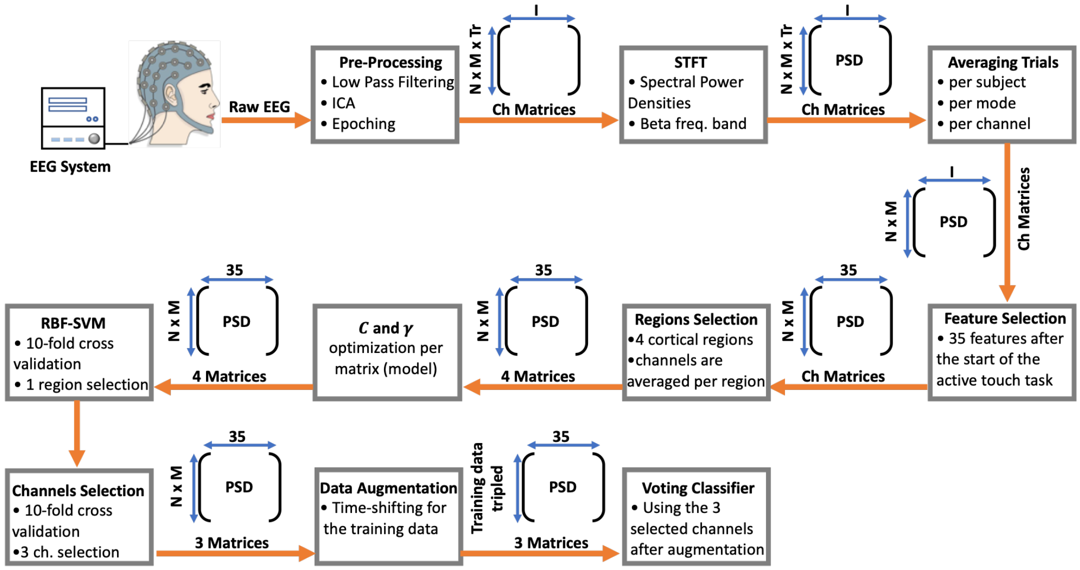


Fig. 3. Implementation of the EEG data processing and classification block diagram

tactile stimulation from an electronic pad was delivered to the participating subjects. The pad is capable of controlling the presence or absence of friction-based tactile simulation. This stimulation is achieved by modulating the surface friction between a fingertip and a physical display panel to simulate surface texture. Tactile touch-screen devices provide tactile feedback using electrostatic attraction of fingertip skin to a charged surface [31] [32]. Participants performed an active touch task by touching a virtual guitar lines on a tactile display device (Tanvas Touch). Participants moved their index finger from the start point to the end point within one second of the active touch task, at this time the friction based tactile simulation is enabled or disabled randomly. These conditions are called with/without tactile simulation modes. EEG signals were recorded during the experiment. After the data was recorded, band pass filtering was performed to ensure that the frequency range of the EEG signals are between (0.1–55 Hz). Also, each signal was divided into epochs corresponding to with/without tactile stimulation. After pre-processing, spectral power densities of beta band (13–30 Hz) were computed using short time Fourier transform (STFT) over 70 time-indices. The experimental procedure and participant recruitment were reviewed and approved by New York University Abu Dhabi Institutional Review Board (IRB 073-2017) and a written consent was obtained from all participants.

IV. Results and Discussion

For each of the 4 models, both C1 and C2 (the SVM parameters) were optimized using Grid Search Scores method; a 9 by 9 combination of values for C1 and C2 are tested and compared. This is an important optimization step before training the RBF-SVM model. Figure 4 shows an example of an optimization grid for one of the SVM models. A pattern of worse performance was noticed for high values of C1 across the models. The 4 SVM models corresponding to the 4 cortical regions were trained and tested using 10-fold cross validation and utilizing the optimum C1 and C2 obtained for each model. The data was shuffled to reduce variance and ensure that over-fitting is avoided as much as possible. The accuracy of each of the models (each region has its own model) was calculated. Relative higher accuracy of a model compared to the rest of the models indicate the importance of the corresponding region in the classification procedure. Thus, the accuracy of the classifier served as a deciding parameter to select the most relevant brain region. The highest classification accuracy was realized from the middle frontal cortex with 68% classification accuracy compared to only 60% from the other three brain regions. This is in agreement with our previous study [18] in which a manual statistical significance test on beta band PSD at the middle frontal cortex showed a noticeable statistical significance with $p < 0.01$. The manual statistical significance test showed other neural markers of the tactile features. However, beta band activation at the middle frontal cortex showed the largest distinction in the EEG pattern. Also, beta activity in the mid-frontal cortex relates to the cognitive processing of the tactile experience which is important in the evaluation process of the haptic experience. For the aforementioned reasons, we focus on beta band activation at the middle frontal cortex.

We identified three channels in the mid-frontal cortex that associate the most with tactile features: AF3, AF4 and F1. We formed a voting classifier out of the three identified channels in which the classification decision is taken by the three corresponding classifiers. An RBF-SVM model was trained using the EEG data from AF3, AF4 and F1. Both, C1 and C2 were optimized to create the best separating boundary between the data of the two modes; C1= 2.8 and C2 = 0.0073.

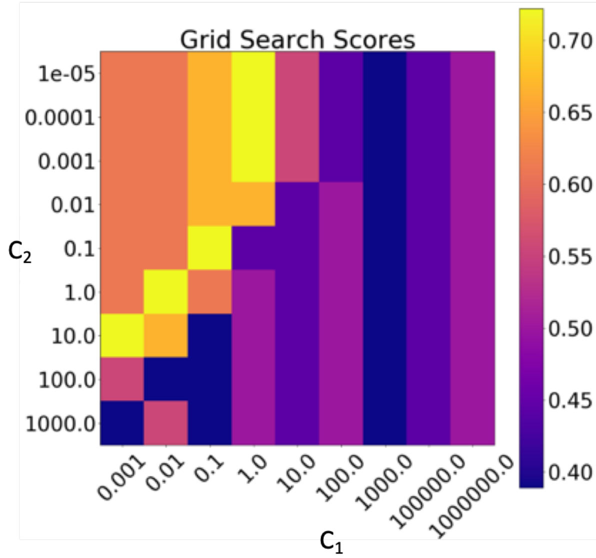
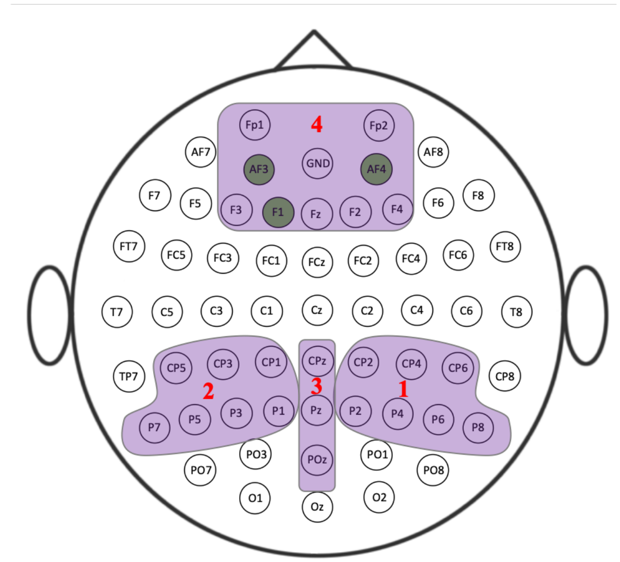


Fig. 4. Grid search for the best C1and C2 values for AF3 EEG channels in beta band. The thermal bar indicates classification accuracy



Region	Classification Accuracy	
	Mean	Standard Error
Ipsilateral Parietal (Region 1)	61 %	9.3 %
Contralateral Parietal (Region 2)	60 %	7.0 %
Middle Parietal (Region 3)	60 %	3.4 %
Middle Frontal (Region 4)	68 %	6.6 %
AF3, AF4, F1 channels	73 %	6.5 %
AF3, AF4, F1 with time-shift data augmentation	85 % *	3.3 %

Fig. 5. Cortical brain regions and summary of the classification accuracy. (*Wilcoxon signed-rank test, p = 0.0156)

An improved classification accuracy of 73% was obtained. One of the main obstacles in EEG classification problems is the small number of observations (i.e: participants/subjects). This leads to poor classification accuracy due to the scarcity of the training data. One solution that is commonly used in deep-learning image classification field is data augmentation; training data is populated by creating modified versions of the available images without altering their labels. In time-series based data, other augmentation techniques exists such as window slicing, window wrapping [28] [29] and time-shifting [33]. To the best of our knowledge, these methods were not applied on EEG time-series data before. Care should be taken while selecting the appropriate augmentation technique such that it doesn't change the label/class of the augmented data. Thus, we propose to use time-shifting based augmentation in which the training data (each trial) is either shifted forward or backward in time with a small amount; such alteration is appropriate for EEG signals because these shifts in time can occur between subjects/trials up to few tens of milliseconds. We tripled the size of the training data by shifting each trial 50 ms forward and 50 ms backward. A percentage of 20% of the data was held out for testing. The classification accuracy increased significantly to 85%. Figure 5 shows a graphical representation of the considered cortical regions and the selected channels in the middle-frontal region. Also, a tabulated summary of the mean classification accuracy for the different cases is listed. A statistical significance in the classification accuracy has been found between non-augmented and augmented datasets (Wilcoxon signed rank test, $p = 0.0156$).

The selected brain region presented here is validated by our previous study [18] in which beta band oscillations at the mid-frontal cortex showed a significant difference ($p < 0.01$) between the two modes through manual statistical comparison. The channels AF3, AF4 and F1 were used in a voting classifier. In our case, this was possible because: 1) The selected channels are spatially close and reside above the mid-frontal cortex and 2) These channels have the highest classification accuracy relatively. Employing the spatially close top-performing channels in the mid-frontal cortex in a voting classifier and implementing the time shifting data augmentation scheme both boosted the classification accuracy to 85%.

V. CONCLUSIONS

In this paper, we demonstrated the use of a ML based technique in order to select the most relevant EEG channels and classify EEG data for identifying the presence or absence of tactile feedback during an active touch task. This classification process aims to aid in developing objective evaluation methods for the prominence of tactile features in products that is meant to engage with consumers haptically. A non-linear RBF-SVM classifier was used. We identified that beta activation in the mid-frontal region is the most relevant set of data for this classification. This result is cross validated with the results of our previous study, conducted by manual statistical significance tests. Additionally, we selected the most relevant channels in the mid-frontal region for an easier future experimentation while improving the accuracy of the classification. Voting classifier was employed based on the three selected models (i.e: channels) in the mid-frontal region. Furthermore, we tripled the size of the training data through data augmentation (time shifting) due to which the classification accuracy increased to 85%. We believe that a better classifier can be realized by improving on the quality of the EEG acquired data and by increasing the size of the training data as well. Finally, this study can be considered as a start towards building a hpatic model that is capable of objectively determining the tactile features during a haptic task through which the haptic experience of the subject can be quantitatively evaluated.

VI. ACKNOWLEDGEMENT

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