EEG-BASED TEXTURE CLASSIFICATION DURING ACTIVE TOUCH

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ABSTRACT

Modern approaches to providing haptic feedback focus mainly on robotic manipulators, vibrators, and tactors. This type of feedback tends to be cumbersome and limited to a small number of contact points. On the contrary, electrotactile displays are compact and wearable, and recent discoveries demonstrate that naturalistic sensations of touch can be provided by electrical stimulation of peripheral nerves. Haptic feedback is essential for daily activities, as it allows us to become aware of our surroundings. The aim of this study is to develop techniques to extract EEG features that are markers for real world haptic interactions. The extracted EEG features will be used to model the EEG evidence that will later be employed in the closed-loop guidance system to adaptively control the electrical stimulation. In this work, twelve healthy subjects were recruited to perform a tactile stimulation experiment. Each subject was instructed to use their index finger to rub or tap 3 textured surfaces having varying levels of roughness (smooth flat, medium rough, and rough). EEG and force data were collected synchronously during each movement condition. Analysis of the EEG data showed that the amplitude of the EEG segment and the total power in the Mu (8- 15 Hz) and Beta (16- 30 Hz) bands could be used to identify the roughness of textures using EEG data. We used a 10-fold cross validation to train a 3-class Support Vector machine classifier with chance level of 33%. The results show that it is possible to discriminate EEG activity with very high accuracy among surfaces with different textures.

Index Terms— One, two, three, four, five

1. INTRODUCTION

Haptic feedback through touch plays an integral role in cognitive, social, and biological development [1]. The information collected through haptic feedback is employed to identify, grasp, evaluate, and manipulate objects, from tools to fruits. Haptic perception through touch can be categorized into material and geometric perception. Geometric properties describe the structure of the object, such as size and weight, while the material describes surface properties, such as texture roughness, stickiness, or friction [1]. Roughness is one of the most important features in the perception and discrimination of textured surfaces [2, 3]. Cortical processing of roughness discrimination follows two schemes, cognitive based and sensory processing. The first generates activation in the prefrontal area while the second involves mostly the somatosensory area [1].

Haptic perception of tactile stimuli through touch is a dynamic process that requires movement against a surface to explore its features [1]. It is difficult for a person to discriminate between similar surfaces in roughness without this movement [1, 4, 5].Mechanoreceptors are the main source of touch perception. During active stimulation of the skin, both slowly and rapidly adapting mechanoreceptors contribute to the touch sensation process. The signals originate from the mechanoreceptors in the skin and goes to the thalamus. After that, these signals travel from the thalamus to the primary somatosensory cortex [6, **?**]. The somatosensory system is organized in a contralateral fashion, where the signals sent from the right side of the body project to the left hemisphere and signals from the left side project to the right hemisphere [**?**]. Research on haptic perception has been increasing during the last decade [7, 8, 9, 10, 11]. A number of fMRI studies investigated the somatosensory response to different tactile stimuli. These studies showed that there is a relation between the intensity of the stimulus and the activated volume of the cortex [12, 13, 14].

Neuroimaging techniques such as functional magnetic resonance imaging (fMRI) imaging provide high spatial resolution, however it is difficult and costly to study tactile stimulation and processing in the brain using fMRI. Also, fMRI suffers from low temporal resolution. On the other hand, Electroencephalography (EEG) is a low cost and portable alternative to fMRI for investigating brain activity related to tactile stimulation. EEG has high temporal resolution making it a useful tool to analyze the cortical changes in individuals while exploring different textures.

Until recently, most of the studies that attempt to investigate the cortical activity associated with touching textured surfaces while recording EEG involve passive touch only [7, 9, 8]. Passive touch indicates that the participants index finger is at rest while vibro-tactile stimuli are applied on the index. A device that provides a passive stimulation which mimics the movement of sliding an object against a participants while recording EEG was developed [7]. The study showed

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an increase in the power of the theta band (4-7 Hz) for 500 msec after the stimulus onset, followed by a decrease in the power of the alpha band. A following study by the same group showed a linear decrease in the alpha band amplitude with increasing roughness of the stimulus [8]. When studying the brain response to different natural textures, there was a significant relation between the power in the beta band and the discrimination between pleasant (soft) and unpleasant (rough) textures [9].

The majority of research studies focused on passive touch and suggested that passive touch, compared to active touch, elicits greater magnitude responses in the somatosensory cortex [15]. A recent study using fMRI found greater activation for active touch while studying the underlying neural mechanisms of active and passive touch [10].

An attempt to compare the cortical activity involved in active and passive touch using EEG was proposed by Monungou et.al [11]. They used a device that produces ultrasonic waves which modulates friction at a frequency of 11 Hz, producing a tactile percept that mimics a square-wave grating. This device was used while the participant was freely exploring the surface, active touch, and while his finger was at rest, passive touch. A force feedback-controlled robot was used to reproduce, in the passive touch condition, the exact movements and normal force during the active touch condition. The Somatosensory Evoked Potential were recorded, and the brain activity at the frequency of the friction modulation in both active and passive touch was compared. Analysis of recorded force data confirmed that both passive and active touch conditions were matched. The recorded EEG over the central and parietal electrodes, contralateral to the stimulated fingertip, showed that the measured Somatosensory Evoked Potentials were highly similar in both conditions.

The research objective of this study is to identify and analyze EEG features associated with active touch of surfaces having varying degrees of roughness. Then salient EEG features that enable discrimination among EEG signals corresponding to different textures, will be extracted.

2. MATERIALS AND METHODS

2.1. Experimental Procedure

2.1.1. Participants

A total of twelve right-handed healthy participants aged between 23 and 31 years (4 males and 8 females), were recruited and provided written consents (University of Pittsburgh IRB No. PRO17040151). None of the participants suffer from skin allergies, neurological, or psychiatric diseases and none of them have metal or electronic implants. The subjects were seated comfortably in front of the system as shown in Fig.1 .

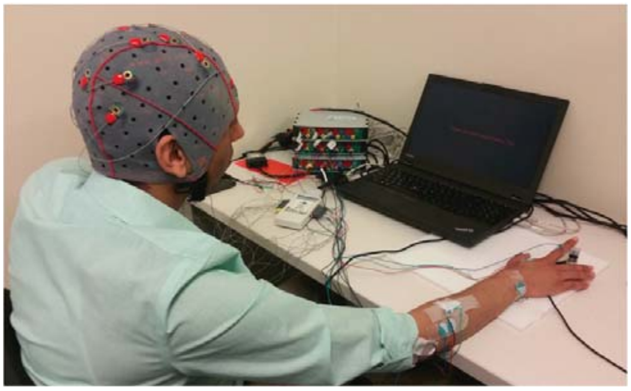

Fig. 1: Experimental Setup. The participant is tapping the texture mounted on the force transducer.

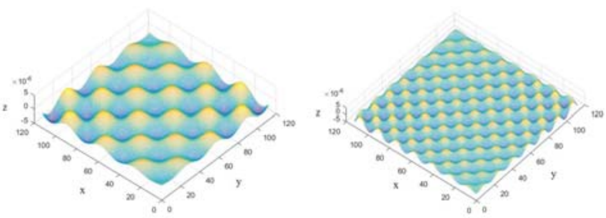

Fig. 2: Medium rough and rough surfaces respectively.

2.1.2. Materials

A set of three textures with different levels of roughness (flat, medium rough, and rough surfaces) have been generated using MATLAB and fabricated with 3D printing. The power spectral density of each surface is given by :

$$\phi(|k|) = \begin{cases} C, & \text{if } k_l <= |k| <= k_r. \\ C(\frac{|k|}{k_r})^{-2(1+H)}, & \text{if } k_r <= |k| <= k_s. \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

where C is the roughness amplitude, k_l, k_r, k_s are the lower roll-off and upper cutoff wave numbers and H is the Hurst roughness exponent. Figure 2 shows both the medium rough (H = 0.5, C = $10 * 10^{10}$ k_l = k_r = 16, k_s = 64) and rough (H = 0.5, C = $10 * 10^{10}$ k_l = k_r = 32, k_s = 256) surfaces used in this study.

2.1.3. Data Acquisition

EEG was recorded according to the 10-20 system from 14-channels, using electrodes placed over the frontal and somatosensory cortex focusing around the sensorimotor integration regions, respectively (F3,F4, FC3, FC4, C1, C3, C5, CZ, C2, C4, C6, CP1, CPZ and CP2). The left mastoid was used as a reference and FPz as the ground electrode. In this study, two g.USBamp (from g.tec medical engineering GmbH) amplifiers were used, one for EEG data acquisition and one for force data. The EEG data were digitized with 1200 Hz sampling rate. EEG signals were filtered using the amplifier's own filters of a 4th order notch filter with corner frequencies of 58 and 62 HZ, and an 8th order band pass filter with corner frequencies of 2 and 62 Hz. EEG data was further preprocessed using FIR bandpass filter designed using Kaiser window with corner frequencies: 8, 60 Hz. Force data was recorded from the NANO17 F/T transducer, (ATI Industrial Automation, USA), then transferred to the analog inputs of the g.USBamp amplifier. Similar to EEG data, Force data was digitized with 1200 Hz sampling rate and filtered with the same amplifier's filters. Synchronization of both EEG and force data was done by synchronizing the two amplifiers. More specifically, the presentation software (Psychtoolbox) sends triggers to the amplifiers to mark the "go" cue for each condition and the time stamp for each trigger is saved[16]. These triggers are then used to segment both the EEG and force data.

2.1.4. Experimental setup

The experimental setup is shown in Fig.1. The first part of this study was to identify the EEG channels that would be most responsive to haptic input through electrical stimulation. This is done by applying an electrical stimulation (3 mA pulses with 1 Hz frequency for 30 seconds) to the right index finger of the participants while recording EEG. The electrical stimulation was provided by the LG-3000 TENS Unit(TENS Pros, MO, USA). In the second part, three textures with different levels of roughness (flat, medium rough and rough surfaces) were used. These surfaces were securely attached to a force transducer which was fixed on a table. The induced force and EEG were recorded synchronously while the participant was rubbing or tapping each surface for one minute. We denoted one complete rub/tap over the surface as a trial and used the recorded force data to segment the EEG for different trials. We have 18 different conditions, a combination of movement type (rub/tap) speed (slow, medium speed, and fast) and three textures. Each participant was trained before the experiment to rub or tap each surface with one of three different speeds (0.5, 1, and 2 Hz) , and then instructed to follow the trained speed for one minute per each condition. The 18 conditions were randomized for each participant, and there was one minute of rest after each condition. We denoted one complete rub/tap over the surface as a trial and used the recorded normal contact force component to segment the EEG for different trials.

2.2. Data Analysis

2.2.1. Force Data Analysis

The normal force component was analyzed to segment each trial, which denotes a complete rub or tap movement. A threshold value was selected per each condition, and if the force data at any time was greater than this value it was multiplied by one, otherwise by zero. The segmented force data is then used to segment the corresponding EEG data.

2.2.2. EEG Data Analysis and Feature Extraction

For the first part of the study, the Power spectral density of the 14 channels were calculated, and the channel with the highest power was chosen to be the most responsive channel to haptic electrical stimulation for each participant.

For the second part of the study, the indices of the segmented force data were used to mark the 14 channels of the recorded EEG. For each trial, we extracted features based on the spectral properties of the corresponding EEG segment. More specifically, the normalized total power in the Mu (7-12 Hz) and the normalized total power in the Beta (13-30 Hz) bands were calculated. Also, the average EEG amplitude across time for each trial per channel was calculated. These three features were standardized and concatenated to form a feature vector that was used in classification. The classification results for the most responsive channels identified from first part are compared to the classification results obtained from the other EEG channels.

2.2.3. Classification

In order to evaluate the effectiveness of the selected features in discriminating surfaces with different textures using EEG, a Support Vector machine classifier (SVM) was used to perform the classification task [17]. SVM basically aims to find an optimal hyper-plane (usually through kernel transformation to enable linear separation) that categorizes new observations by formulating an optimization problem using the training observations. In this paper, a second order polynomial kernel with scale of one and offset of zero was used. A 3-class SVM classifier was used to discriminate between the textured surfaces (flat, medium rough, and rough). We used 10-fold cross-validation to train the SVM classifier with chance level of 33%.

3. RESULTS AND DISCUSSION

3.1. Electrical Stimulation

The Power spectral density of the 14 channels for one of the participants is shown in Fig. 2. In this figure, the electrode located at C5 is identified as the most responsive channel based on the power spectral density of the recorded EEG. channel. As the participant was right- handed and the stimulation was applied to the right hand, we expected observing sensitivity in the channels located in the left-hand-side of the somatosensory cortex, and the results confirmed our expectations. For the rest of participants, the most responsive channels were either one of C3, C5, FC3, aor F3. These electrodes are located around the contralateral sensorimotor area, which is responsible for sensation in the brain.

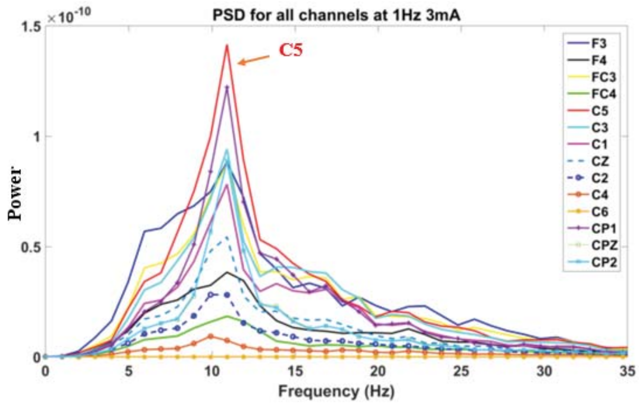

Fig. 3: Power spectral density of EEG in response to electrical stimulation

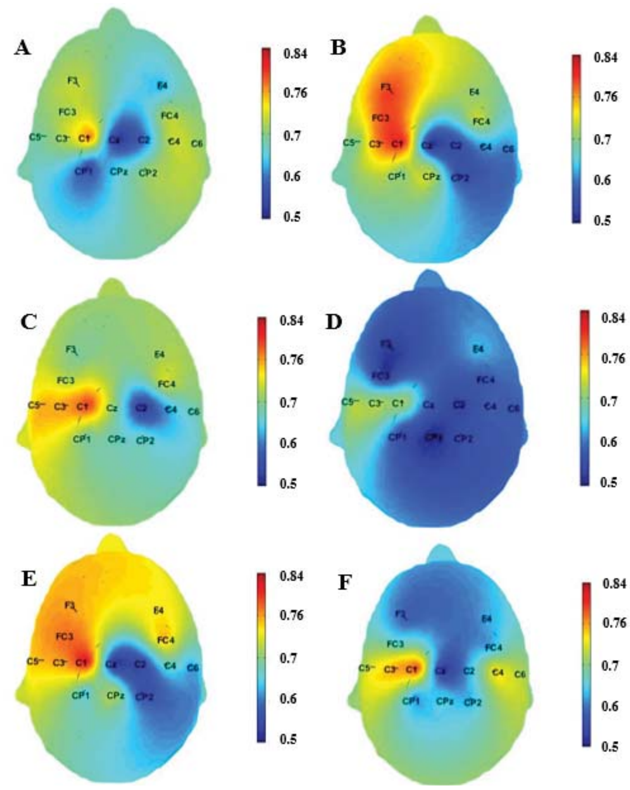

Fig. 4: Heat map for the accuracy values at each electrode location, where each condition is as follows, A: Rub Fast, B: Rub at medium speed, C: Rub slow, D: Tap Fast, E: Tap at medium speed and F is tap slowly.

3.2. Texture Classification

The mean and standard deviation of the accuracy and sensitivity of the three textured surfaces for the 3-class classification across all participants calculated at the corresponding most responsive channels (as identified from the first part of the study) are shown in Table 1 for the rub movement and Table 2 for the tap movement. For both the rub and tap conditions, the sensitivity of the EEG features discriminating a textured surface increased with the increase in roughness level. In the rub condition, the the accuracy increased with the decrease in speed. Similarly in the tap condition, the slow speed achieved higher accuracy than both fast and medium speeds. This could reflect the increase of the participant's ability to discriminate between textures as touching speed decreases. We also compare the classification accuracy across all the channels. Specifically, heat maps for the accuracy values at each electrode location for each condition averaged across all participants are shown in Fig.4. It can be seen that the electrodes that are located around the contralateral sensorimotor integration regions have the highest accuracy values. It is worth mentioning that these EEG features could be affected by the motor component in the EEG signal, thus, future work will include more investigation into minimizing the effect of the EEG motor component.

Table 1: The mean and standard deviation of the accuracy, sensitivity of each class (Flat, medium and rough surfaces) averaged across all the participants calculated at their most responsive channel for the Rub movement condition. S1: Flat, S2: Medium Rough and S3 is the Rough surface.

Speed	Fast	Med-Speed	Slow
Accuracy	88.21 ± 0.01	89.47 ± 0.01	90.2 ± 0.01
Sensitivity (S1)	79.5 ± 5.98	82.03 ± 7.35	83.33 ± 6.47
Sensitivity (S2)	82.69 ± 4.69	85.15 ± 2.49	87.323 ± 2.6
Sensitivity (S3)	92.7 ± 1.5	93.2 ± 0.85	94.67 ± 0.73

4. CONCLUSION AND FUTURE WORK

In this paper, we showed that using EEG it is possible to classify different textures during active touch. We performed experiments with 12 healthy subjects and recorded EEG while they actively touched (with their index fingers) three different textures under different touching (rub or tap) and speed (low, medium and high) conditions. We showed that EEG features based on the amplitude of the EEG and total powers in Mu and Beta band enabled classification of different textures with very high accuracy. The accuracy increased with

Table 2: The mean and standard deviation of the accuracy and sensitivity of each class (flat, medium and rough surfaces) averaged across all participants calculated at their most responsive channel for the Tap movement condition. S1: Flat, S2: Medium Rough and S3 is the Rough surface.

Speed	Fast	Med-Speed	Slow
Accuracy	86.8 ± 0.04	84 ± 0.065	87 ± 0.012
Sensitivity (S1)	83.68 ± 5.45	82.37 ± 5.94	82.81 ± 6.18
Sensitivity (S2)	84.26 ± 4.25	81.85 ± 4.42	85.36 ± 1.47
Sensitivity (S3)	87.38 ± 1.36	82.54 ± 3.77	87.59 ± 0.97

lower speed of interaction and as the roughness of the surface increased. Moreover, we showed that EEG channels that are most responsive to electrical stimulation to index fingers of participants are also the channels that provide high classification accuracy. In summary, the aim of this study was to develop analysis techniques to extract EEG features that could classify various textures with different levels of roughness using EEG. These EEG features will be used to design principles for model-based optimal EEG-guided closed-loop haptic feedback in our future work.

5. ACKNOWLEDGEMENTS

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