IDENTIFYING MOVEMENTS FROM ELECTROCORTICOGRAPHY

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INTRODUCTION

Brain-computer interfaces (BCI) use brain signals to control electronic devices. These devices promise to assist individuals with severe mobility impairments such as advanced stages of amyotrophic lateral sclerosis (ALS), brain stem stroke, spinal cord injury, and severe cerebral palsy [1].

Recently, BCI technology has been used as an assistive device to restore movement. This is accomplished by controlling an orthotic, prosthetic or neuroprosthetic device through the BCI. For a transparent and intuitive operation of these devices through a BCI, it would be ideal to use neural activity which is correlated with the desired output to command the device and that does not require user training. For example, if a user wanted to open a prosthetic hand, the BCI would identify changes in brain activity resulting from the desire to perform this action and generate the appropriate movement. This type of correlation between neural signals and behaviour has been found when a person is engaged in voluntary movement (performed, imagined, or during preparation to perform a movement).

One of the strategies that researchers have applied to use a BCI system to restore movement has focused on the identification of specific movements. This has included the detection of imagined and performed movements as well as the intention to perform these movements using both EEG and ECoG signals. By using ECoG recordings, it has been possible to identify extension of the middle finger, palmar pinch, tongue protrusion and lip protrusion [2, 3], wrist extension, target tracking, finger sequencing and threading [4, 5] movements, hand and face movements as well as verbalization [6, 7].

The purpose of this study was to explore the possibility of identifying specific movements performed by an individual from ECoG recordings obtained with subdural electrodes with four contacts. The movements were performed using the same upper limb and likely involved areas of the body with close or similar representations in the motor cortex. A feature extraction algorithm was developed that was able to determine which arm movement was performed based on the ECoG recordings. These recordings were performed using standard subdural four-contact electrodes placed over the primary motor cortex.

MATERIALS AND METHODS

<u>Participants</u>

Two individuals participated in this study. Subject 1 was a 73 year old male individual with Parkinson’s Disease, and subject 2 was a 65 year old female individual with Essential Tremor. Both participants were recruited from the Movement Disorder Clinic of the Toronto Western Hospital and gave written informed consent to participate in the study, which was approved by the University Health Network Research Ethics Board.

Both participants received a system for direct brain stimulation for the treatment of tremor. This procedure began with the implantation of subdural electrodes (figure 1) followed by a period of several days in which the electrode leads were externalized and the characteristics of the electrical stimulation (i.e., amplitude, polarity, etc.) were fine tuned. This was followed by implantation of the pulse generator and permanent internalisation of the entire stimulation system. The study presented in this article was conducted during the time period when the electrode leads were externalized and at least two days after the electrodes were implanted.

The subdural electrodes were implanted over MI area associated with the upper extremity representation. This was confirmed by applying electrical stimulation (100 Hz, 100 µs, monopolar, 3-10 mA) and observing contractions of the muscles on the contralateral upper limb. Direct stimulation of the motor cortex elicited movements consistent with elbow flexion and closing the hand for subjects 1 and 2, respectively. For both participants, the electrodes were implanted for clinical and investigational reasons independent of the study presented here.

Experimental Protocol

The participants of this study performed upper limb movements with the arm contralateral to the site of electrode implantation. Subject 1 performed elbow flexion (EF) and reaching to targets positioned 30 cm to the right and left of the subject's midline (RTR and RTL, respectively). Subject 2 performed the reaching tasks as well as closing the hand (CH). The movements were performed following an auditory cue ("Go").

The limb kinematics and monopolar ECoG signals were recorded simultaneously while each individual performed the movements. Each movement was repeated 30 times.

Feature Extraction

Labeling the subdural electrode contacts *ECoG1*, *ECoG2*. *ECoG3*, and *ECoG4*, the ECoG monopolar signals were subtracted between adjacent (e.g. *ECoG2*- *ECoG2*) and non adjacent (e.g. *ECoG3*- *ECoG2*) contacts.

The time-frequency distribution was estimated for all ECoG signals (monopolar and differential). To do this, each signal was divided into segments of 640 msec (128 samples) by applying a Hamming window.

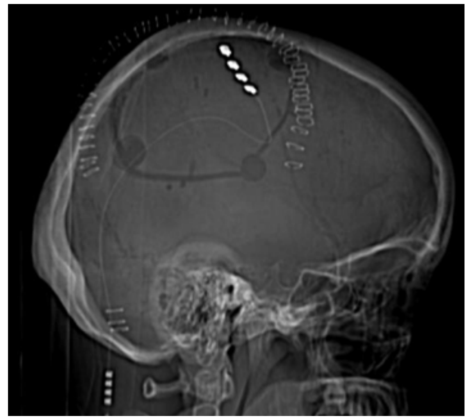

Figure.1. X-ray image showing the implanted subdural electrodes for subject 2. The electrodes used ('Resume', Medtronic 3586, Minneapolis, MN) consisted of four platinum contacts of 4mm in diameter and a centre to centre distance of 10mm, arranged in a single row.

A Fourier transform was then computed for the windowed ECoG signal resulting in a spectrum with a resolution of 1.56 Hz. Then the window was shifted to the right by one sample and the procedure was repeated until the end of the ECoG signal was reached. Once this process was completed, a Pearson correlation coefficient was calculated between each one of the time-resolved spectral components of the resulting spectrogram and each one of the position kinematic signals (X, Y, and Z). Correlation coefficients with an absolute value grater than 0.1 were considered significant ($p<0.01$; degrees of freedom of statistics were 600). For each of the kinematic components, we identified the 20 frequency components with the highest absolute correlation coefficients. These frequencies were grouped using a histogram with bins representing bandwidths of 10 Hz. A different histogram was created for each one of the three kinematic coordinates of the executed movement.

The magnitude of each bin in the histogram indicated the probability that the frequency it represented was correlated with the movement performed by the subject at the time of the recordings. The probability estimate was defined as the number of spectral components within a frequency bin found to be correlated with movement divided by the number of frequency components included in the entire histogram (i.e. 20). Figure 2 shows an example of the end result of this process.

Classification Tests

To determine off-line the movement (i.e. EF, CH, RTR, RTL) performed by the individual by observing the ECoG features of a single trial using the process described above we used a nearest neighbour classifier (NCC). The magnitude of each column in the histograms was defined as a feature for the NNC; for any given motor task, all of the features for each kinematic signal (X, Y, and Z) were concatenated to form a single feature vector.

The classifier was trained using 5 trials, 20 spectral components (sorted in descending order according to their absolute value as describe previously). We investigated the effect of the type of ECoG signals used by the classifier (i.e., monopolar, differential adjacent, or differential nonadjacent signals) on the classification accuracy.

RESULTS

Each one of the movements generated a unique histogram for each of the kinematic dimensions, as shown in figure 3. The histograms were also subject specific. The correlation coefficients between the kinematic recordings and ECoG spectral components used were in the range of 0.15 ± 0.006 to 0.63 ± 0.01 (mean $\pm$ SD).

The classifier was able to identify the movements performed by each subject with an accuracy of 89%. The accuracies achieved using differential adjacent and differential nonadjacent signals were significantly greater than those achieved using monopolar signals ($p<0.05$; Wilcoxon ranksum test). The best accuracies were obtained using non adjacent differential signals.

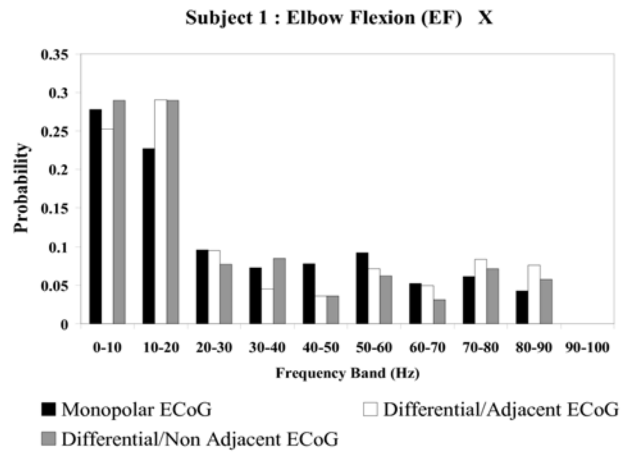

Figure 2. Distribution of ECoG frequency components correlated with the X-coordinate while subject 1 was performing elbow flexion (EF). Example of the histogram representing how often spectral components of the ECoG signals within the different frequency bins were found to be correlated with the X-coordinate while subject was performing EF.

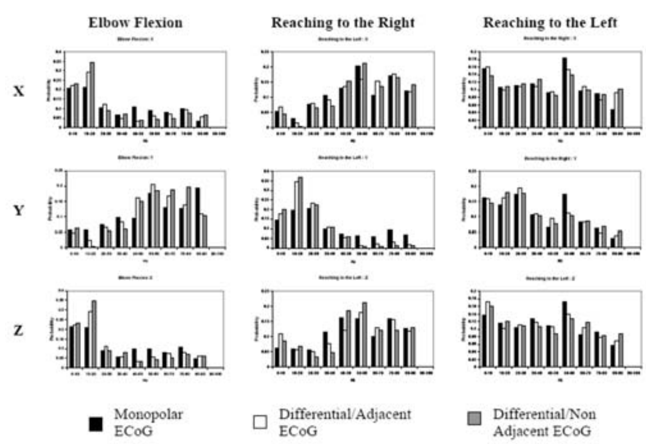

Figure. 3. Histograms obtained using frequency bins of 10 Hz for Subject 1. Each one of the movements generated a different histogram for each one of the coordinates.

CONCLUSSIONS

A novel method for the identification of specific motor tasks from ECoG signals was presented. The process described here simple; it is based on creating histograms representing the probability of correlation between spectral components of ECoG signals within predefined frequency bands and kinematic components of movement. Details of this work can be found in [8]. The distribution of the spectral components was found to be unique for the different motor tasks. This allowed the use of the histograms as features to classify ECoG signals according to the specific movement that an individual had performed. The distributions of ECoG spectral components correlated with movement were different for the two participants in this study. This finding suggests that the ECoG features that can be used for the identification of specific motor tasks are subject specific.

The current implementation of this system requires that the user performs the kinematic task to perform the classification Our immediate future work will be focused on developing a classifier that will be able to perform the classification while the motor task is being executed.. Our long-term goal is to apply this classification method to imagined movements.

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