Identification of arm movements using correlation of electrocorticographic spectral components and kinematic recordings

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Abstract. The purpose of this study was to explore the possibility of using electrocorticographic (ECoG) recordings from subdural electrodes placed over the motor cortex to identify the upper limb motion performed by a human subject. More specifically, we were trying to identify features in the ECoG signals that could help us determine the type of movement performed by an individual. Two subjects who had subdural electrodes implanted over the motor cortex were asked to perform various motor tasks with the upper limb contralateral to the site of electrode implantation. ECoG signals and upper limb kinematics were recorded while the participants were performing the movements. ECoG frequency components were identified that correlated well with the performed movements measured along 6D coordinates (X, Y, Z, roll, yaw, and pitch). These frequencies were grouped using histograms. The resulting histograms had consistent and unique shapes that were representative of individual upper limb movements performed by the participants. Thus, it was possible to identify which movement was performed by the participant without prior knowledge of the arm and hand kinematics. To confirm these findings a nearest neighbour classifier was applied to identify the specific movement that each participant had performed. The achieved classification accuracy was 89%.

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1. Introduction

Brain-computer interfaces (BCI) use signals from the brain to control electronic devices such as computers. Public and scientific interest in this technology is based on the potential for these devices 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 [1,2].

There are three fundamental components of a BCI: an input (i.e., brain signal), an output (i.e., control command to an external device), and a translation stage that transforms the input into the output (1). Brain-computer interfacing is an emerging field and researchers are still asking fundamental questions such as which type of brain signals are most useful, how to decode or classify these signals, which features of these signals to use to perform the classification or decoding, and what the potential applications of BCI systems might be.

One of the most prominent questions in the field of BCI is which neuronal signal, or group of signals, is optimal for use as an input to BCI [3]. The types of brain signals that have been used as input to a BCI can be classified as magnetic [4,5], metabolic [6] and electrical [1]. Of these, electrical signals have been used most extensively. The electrical activity of the brain is characterized by ongoing oscillatory activity that has been divided into frequency bands. Some of the primary oscillatory rhythms include the delta rhythm (<4 Hz), the alpha or sensorimotor mu rhythm (8-13Hz), the beta rhythm (13 Hz-35Hz), and the gamma rhythm (>35 Hz) [7].

The existing BCI systems can be generally divided into two main categories: 1) systems that require the user to produce a specific mental state to generate a desired command that can be used to trigger an event (e.g. move a cursor on a screen), and 2) systems that extract information about the movement kinematics from the brain signals and use this information to generate a similar or identical movement with a prosthetic or a robotic device. Currently, many examples of BCI systems that require the user to produce a specific mental state exist. The mental state produced by the user is not necessarily related with the behavioural outcome. For example a person imagines moving the tongue to move a computer cursor [8]. The different mental states are detected as changes in brain activity which can be recorded using different techniques such as electroencephalography (EEG) and electrocorticography (ECoG). EEG records the activity of the brain using scalp electrodes and ECoG signals are recorded with subdural electrodes. These are macroelectrodes placed surgically on the surface of the brain underneath the dura. The changes in brain activity convey the user's intentions. Some of the features that have been used to detect different mental states include slow cortical potentials (SCP) [9-12], P300 potential [13-17], as well as changes in power (amplitude) of oscillatory rhythms [18-20]. These systems have been used successfully to control computer cursors in one and two dimensions [1,8,19-21] , generate text [11,13,22,23], and to select from a small set of options (e.g., yes/no) [15,17]. These implementations of BCI's are characterized by a small communication bandwidth making them suitable for providing assistance in communication to individuals who have lost all ability to perform voluntary movement, such as individuals with locked-in syndrome.

Recently, there has been an increased interest in exploring the use of BCIs to restore movement in individuals with paralysis. This broadens the clinical population that can benefit from BCIs to include individuals with spinal cord injury or stroke. Inherently, this application carries the notion of using prosthetic devices, functional electrical stimulation systems, and external actuators (such as a robotic arm) as an extension or substitution of a body part that is affected by the disability. 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. For example, if the desired action was to open a prosthetic hand a BCI user would only have to focus on opening his or her own hand and the BCI would detect changes in brain activity resulting from the intention of opening the hand and would perform the desired action. It has been shown that this type of correlation between neural signals and behaviour can be found in an individual engaged in voluntary movement (performed, imagined, or during preparation to perform a movement).

The current challenges facing BCIs intended for restoration of movement are the detection and estimation of kinematic information as well as identification of specific movements. Some of the most important results in the detection and estimation of kinematic parameters in brain activity come from recordings of populations of single neurons using micro electrodes. The firing frequency of neurons in the primary motor cortex [24-26] has been decoded to generate continuous control signals using both linear and nonlinear algorithms. With this approach it has been possible to control a computer cursor in two [24, 27] and three dimensions [26] (within a simulated/virtual three-dimensional space), and control a robotic arm [26, 27]. This work has been conducted with monkeys and more recently with human participants [27, 28].

There are still important concerns regarding the stability and reliability of long-term single neuron recordings. Two alternatives to recording the activity from individual neurons are local field potentials (LFP) and ECoG recordings. LFPs are recorded using the same microelectrodes used to record the activity of individual neurons but they record the activity of a group of neighbouring neurons. The analysis of LFPs and ECoG signals has shown that changes in amplitude of several frequency components in these signals reflect some kinematic aspects of arm movements. These kinematic parameters include amplitude (range of motion) [29], direction of movement [3, 29-32], velocity, and position [33].

The detection of specific movements has included imagined movements, performed movements, and the intention to perform these movements. Using EEG recordings it has been possible to discriminate between imagination of finger, tongue, left and right hand movements [34] as well as the intention to generate shoulder or elbow isometric contractions [35]. Using ECoG recordings, it has been possible to identify extension of the middle finger, palmar pinch, tongue protrusion and lip protrusion [36, 37], wrist extension, target tracking, finger sequencing and threading [38, 39] movements, hand and face movements as well as verbalization [40, 41]. It has also been possible to identify the body part (tongue, face, arm or leg) used to perform sustained contractions [42, 43].

Recently a system proposed by Pfurtscheller et al. was also capable of discriminating between imagined foot, tongue, left hand, and right hand movements using EEG recordings [18]. The same group has demonstrated that this type of BCI system can be used to control orthotic [44], prosthetic or neuroprosthetic [23, 45, 46] systems that would operate as state machines [47].

Today we can confidently say that recordings from micro electrodes implanted in the motor cortex can be used to extract reliably, and in real-time, upper limb kinematics. However, it remains unknown if similar information can be extracted using a system that applies significantly less specific recordings, such as ECoG recordings. There are at least two advantages for using ECoG-based system. First, ECoG electrodes are minimally invasive, especially those with four or six contacts, and have been used extensively and reliably for diagnostic and treatment purposes in the past [48, 49]. Second, using four or six recording sites dramatically simplifies the BCI system design and makes the system more feasible from engineering and clinical perspectives. Few recent studies have tried to address this challenge. Some studies have been able to demonstrate that specific movements can be identified from ECoG recordings using 16 to 126 ECoG electrodes. Graimman et al. [37] were able to identify specific movements using a single ECoG electrode. However, they first had to implant a group of 63 to 126 electrodes and through an elimination system were able to select the single electrode used for motor task identification through the ECoG recordings.

The purpose of this study was to explore the possibility of identifying specific movements performed by an individual from four ECoG recordings. 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 executed based on ECoG recordings alone. The ECoG recordings were performed using standard subdural four-contact electrodes placed over the primary motor cortex (MI).

2. Materials and Methods

2.1 Participants

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 with Essential Tremor. Both were recruited from the Movement Disorder Clinic of the Toronto Western Hospital. Neither subject exhibited action tremor or rigidity. They were both medicated at the time of testing. Subject 1 showed mild signs of tremor and subject 2 did not show any signs of tremor after the electrode implantation. The participants 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 (DBI) for the treatment of tremor. This procedure began with the implantation of subdural electrodes 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. Both subjects had electrodes implanted in the left hemisphere. This was followed by implantation of the pulse generator. 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.

2.2 Electrodes

Each participant was implanted with subdural 'Resume' electrodes (Medtronic 3586, Minneapolis, MN) consisting of a single row of four platinum discs (contacts) of 4 mm diameter and a centre-to-centre distance of 10 mm embedded in a silicone membrane (figure 1). Patients underwent craniotomy under local anaesthesia. The electrode strip was implanted over MI area associated with the upper extremity representation. The location of the electrodes was confirmed using electrical stimulation and by observing contractions of the muscles on the contralateral upper limb (100 Hz, 100 ms, monopolar, 3-10 mA) [50]. Specifically, when stimulated subject 1 produced the elbow flexion movement and subject 2 produced the hand closing movement. For both participants, the electrodes were implanted for clinical and investigational reasons independent of the study presented here.

2.3 Experimental Setup

The study was conducted in the Epilepsy Monitoring Unit at the Toronto Western Hospital. The ECoG signals were acquired in a monopolar configuration referenced to Fz using an electroencephalographic digital system (XLTEK, Canada) on a dedicated personal computer with a sampling rate of 200 Hz and a bandwidth limited between 0.3-100 Hz.

The movement of the upper limb was recorded using a six-dimensional (X, Y, Z, roll, pitch, and yaw) electromagnetic movement measurement system (Fastrak by Polhemus Inc., USA) and customized data acquisition software written in Visual Basic. One Fastrak sensor was placed over the dorsal aspect of the third metacarpal bone. Three-dimensional position and rotation of this sensor was recorded at 40Hz. The electromagnetic nature of the measurement system makes it vulnerable to interference from nearby large metallic objects and metallic objects placed between the transmitter and the receiver [51]. Metallic furniture was moved away from the experimental area in an effort to ensure that the recordings were unaffected by these objects. Due to the constraints of working in a clinical environment it was not possible to verify that the kinematic recordings were free of artefacts. However, the temporal information of the movement, which is more important than the magnitude of the movements for the work presented here, was unaffected by near by metallic objects. Data collected by the motion recording system were synchronized with the data collected by the ECoG recording system using a temporal marker.

2.4 Experimental Protocol

ECoG signals and limb kinematics were recorded while each subject performed movements with the upper limb. The motor tasks for subject 1 included elbow flexion (EF) as well as reaching to targets placed 30 cm to the right (RTR) and left (RTL) of the midline. Subject 2 performed reaching tasks RTR and RTL, as well as closing of the hand task (CH). Figure 2 shows the motor tasks that were performed by both subjects. Table 1 shows the ranges of the performed movements. Since the ECoG electrodes were placed in the MI areas responsible for EF (subject 1) and CH (subject 2) tasks, it was an obvious choice to add tasks RTR and RTL to the pool of tasks tested because they involve muscle groups with cortical representations either in the same location or in close proximity to cortical representation of tasks EF and CH.

All the movements were performed with the upper extremity contralateral to the site of electrode implantation while the subjects were sitting comfortably. The users received an auditory warning cue ("ready") followed by an auditory execution cue ("go"). The time between the ready and go signals was randomized between one and three seconds to avoid anticipation by the subjects. After the "go" cue was issued participants performed one of the tasks mentioned above (EF, RTR, RTL and CH). From the moment the "ready" cue was given until the participant completed the task the ECoG signals and movement kinematics were recorded simultaneously. Each movement was repeated 30 times. The durations of each of the motor tasks are shown in table 1.

2.5 Analysis

The kinematic recordings were up-sampled to 200 Hz using cubic spline interpolation and then synchronized with the ECoG signals. The onset of movement was determined by observing the instant at which the magnitude of the movement recordings exceeded a threshold of 5 % of the total movement range. The initial position and orientation were defined as the value of the motion recorded at this instant. For the purpose of analysis, each trial consisted of data starting 1500 ms prior and ending 3000 ms after the beginning of the kinematic recording. A typical trial is shown in figure 3.

Table 1. Duration of movement, Available Trials, and Movement ranges for all kinematic dimensions recorded.

				Range or Motion (Mean ± SD)					
Subject	Task	Duration (s)	No. of good trials	X (cm)	Y (cm)	Z (cm)	ROLL (deg)	YAW (deg)	PITCH (deg)
1	EF	0.94 ± 0.26	13/30	17.4 ± 3.4	5.15 ± 0.8	6.9 ± 0.5	65.8 ± 3.4	64.4 ± 6.2	47.9 ± 3.4
1	RTR	0.94 ± 0.45	8/30	30.2 ± 19.6	25.8 ± 8.8	6.3 ± 1.2	69.4 ± 23.3	58.2 ± 11.1	41.8 ± 8
1	RTL	0.87 ± 0.40	8/30	35.4 ± 4.9	5.43 ± 1.2	2.3 ± 0.6	87.9 ± 3.7	43.1 ± 13.6	22.7 ± 4.1
2	CH	0.99 ± 0.39	13/30	7.3 ± 1.1	5.7 ± 5.6	7.3 ± 3.3	157.6 ± 129.4	75.1 ± 13.7	84.5 ± 44.7
2	RTR	0.74 ± 0.14	9/30	31.8 ± 8.9	40.8 ± 4.7	21.4 ± 2.3	63.6 ± 25.7	27.7 ± 16.7	51.7 ± 12
2	RTL	0.83 ± 0.15	10/30	29.2 ± 10.4	43.5 ± 4.9	20.8 ± 6.6	55.3 ± 14.8	47.7 ± 6.2	43.6 ± 31.1

Each trial was visually inspected to identify mistrials. A mistrial was defined as: 1) a trial in which the individual had performed a movement different to what had been instructed; 2) the participant had started moving before the “go” auditory signal; 3) the movement had lasted more than three seconds; or 4) it was not possible to identify the onset of the movement. Mistrials were excluded from the analysis. The total number of trials available for analysis after removing the mistrials is shown in table 1.

Labelling contacts 1, 2, 3 and 4 of the ECoG electrodes as *ECoG1*, *ECoG2*, *ECoG3* and *ECoG4*, respectively, the following combination of signals were subjected to our analysis:

- four Monopolar (MP) signals: *ECoG1*, *ECoG2*, *ECoG3* and *ECoG4*
- three Differential Adjacent (DA) signals resulting from subtracting potentials of the adjacent electrodes: *ECoG1 - ECoG2, ECoG2 - ECoG3* and *ECoG3 - ECoG4*
- three Differential Nonadjacent signals (DN) representing the difference between potentials of the non-adjacent electrodes: *ECoG1 - ECoG3*, *ECoG1 - ECoG4* and *ECoG2 - ECoG4*

2.6 Feature Extraction

The time-frequency distribution for each ECoG signal was estimated using the following method [29, 52]. Each signal was divided into segments of 640 msec (128 samples) by applying a Hamming window. 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. This resulted in a spectrogram consisting of a matrix in which each row represented the power spectrum of a windowed signal. Each column of this matrix represented a time series of the changes in power at different frequencies. A Pearson correlation coefficient was calculated between each one of these time series and each of the six kinematic signals (X, Y, and Z, roll, yaw and pitch). Any correlation coefficient with absolute value greater than 0.1 was considered significant ($p<0.01$; degrees of freedom of statistics were 600). For each of the kinematic components, we identified the frequency components with the highest absolute correlation coefficients.

The frequencies that were found to be significantly correlated with movement were grouped in a histogram. A different histogram was created for each one of the six kinematic coordinates of the executed movement. We explored four cases for the creation of the histograms: 1) the columns of the histogram had bin widths of 3 Hz (i.e., 0-3 Hz, 3-6 Hz, …, 96-99 Hz); 2) the columns of the histogram had bin widths of 5 Hz (0-5 Hz, 5-10 Hz, …, 95-100 Hz); 3) the columns of the histogram had bin widths of 7 Hz (0-7 Hz, 7-14 Hz, …, 91-98 Hz); and 4) the columns of the histogram had bin widths of 10 Hz (0-10 Hz, 10-20 Hz, …, 90-100 Hz). These widths defined the spectral resolution of the histogram. An attempt was made to use bin widths that would be either narrower or wider than the bandwidth of a common oscillatory rhythm. For example, a 3Hz bin width had a smaller bandwidth than any of the four frequency bands (delta (<4 Hz), alpha (8-13Hz), beta rhythm (13 Hz-35Hz), and gamma (>35 Hz)), while a 5 Hz bin width would cover completely some of the frequency bands.

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 times a frequency bin was found to be correlated divided by the number of frequency components included in the histogram:

$$P_{FreqBin\_i}^{Kin_{jk}} = \frac{\left|FreqBin_{ijk}\right|}{L} \qquad (1)$$

where $|FreqBin_{ik}|$ is the number of spectral components in the *i-th* frequency bin *FreqBin* found to be correlated with the *j-th* kinematic dimension *Kin* of the *k-th* motor task and L is the number of spectral components used to create the histrogram. Figure 4 shows an example of the end result of this process. The entire histogram for kinematic dimension *j* of motor task *k* can then be represented as a vector of probabilities as:

$$\overline{P^{Kin_{jk}}} = \left[P^{Kin_{jk}}_{FreqBin\_1} \quad P^{Kin_{jk}}_{FreqBin\_2} \quad \cdots \quad P^{Kin_{jk}}_{FreqBin\_N} \right]^T \qquad (2)$$

2.7 Classification Tests

We created a system to identify off-line which movement was performed by an individual during the recordings. Our goal was to determine the type of movement (i.e. EF, CH, RTR, RTL) that was performed by the individual by observing the ECoG features of a single trial using the process described above. This was accomplished using a nearest neighbour classifier (NNC), which is an algorithm commonly used in automatic classification problems [53]. The NNC is capable of determining if an item belongs to any previously defined classes, each containing objects with similar characteristics or features. The item's membership is determined by measuring the similarities between its own features and the features of each one of the classes, selecting the class found to have the most similarity. If each one of the features is considered to be a dimension in a multidimensional space it is possible to use geometrical distances, such as the Euclidean distance, to establish similarities. In other words, the class with the shortest distance to the item that is classified is the most similar one.

The magnitude of each column in the histograms was defined as a feature for the NNC; for any given motor task *k*, all of the features for each kinematic signal (X, Y, Z, roll, yaw and pitch) were concatenated to form a single feature vector $\boldsymbol{\theta}_k$:

$$\theta_k = \left[\overline{P^{Kin1k}}\, \overline{P^{Kin2k}} \quad \cdots \quad \overline{P^{KinMk}} \right]^T \qquad (3)$$

where $\overline{P^{Kinjk}}$ is defined by (2).

For each one of the movements performed we selected *n* trials and created their feature vectors (as defined by (3)). These vectors were averaged and used to create the classifier. This process represented the training method for our classifier. The remaining *m*-*n* trials, where *m* represents the total number of trials available for a specific movement, were used to test the classifier (i.e., the trials used to create the classifier were not used to test it). Since the classification accuracy can depend greatly on the specific trials used to create the classifier, we repeated this process of devloping a clasifier 100 times, each time selecting at random the actual *n* trials used to create the classifier [54]. The reported accuracy was defined as the average acuracy of the individual accuracies of the 100 clasifiers developed as part of this process.

The following five effects were statistically analyzed: 1) effect of the number of trials *n* used to train the classifier; 2) effect of the number of frequency components used to train the classifier; 3) effect of the kinematic dimensions used (X,Y, and Z only, or X, Y, Z, roll, yaw and pitch) to train the classifier; 4) effect of the type of ECoG signals used for the training, i.e., monopolar, differential adjacent, or differential nonadjacent signals; and 5) effect of the bin width used to generate the histograms. A Kruskal-Wallis nonparametric analysis of variance was performed on the classifier accuracy to test for dependence against each of the six factors. Statistical significance was set at $p < 0.05$. Then, a multiple comparison test was performed within each factor to identify groups that yielded similar levels of accuracy. Confidence intervals of 95 % were constructed for each factor value and compared.

2.7.1 Effect of the number of trials used to train the classifier. We tested the accuracy of the classifier versus the number of trials *n* used to create the feature vectors for training. More specifically, we started by training the classifier with feature vectors created using a single trial (*n*=1) for each one of the performed movements and tested the classifier accuracy using the remaining data (*m*-*n* trials). Once this process was completed, we created a classifier using feature vectors averaged over two trials (*n*=2) and the accuracy was estimated. This process was repeated until the classifier was trained with feature vectors created with five trials (*n*=5). The data used for testing included trials for all of the movements and was classified off-line. The classification accuracy was defined as the number of trials correctly classified divided by the total number of classified trials.

2.7.2 Effect of the number of frequency components used to train the classifier. We also explored the effect of the number of frequency components on the performance of the classifier. To do this, we trained the classifier using a different number of spectral components (5, 10, 15, 20, 25, 30, 35 and 40), selected according to the magnitude of their correlation coefficient with the different kinematic signals. For example, when five spectral components were used to train the classifier the five frequencies with the highest absolute correlation values were selected to create the histograms. Likewise, the frequency components with the ten highest absolute correlation coefficients were selected when the classifier was trained with ten spectral components. The different values tested for the number of spectral components as well as number of trials used to train the classifier resulted in 40 different tested combinations.

2.7.3 Effects of the kinematic dimensions used. We also investigated the effects of using different kinematic components on the accuracy of the classifier. In other words, we determined if using all of the kinematic components for training and testing the classifier would result in higher accuracy or if better performance would be obtained by using only the X, Y, and Z coordinates. This was done to test the performance of the classifier using a smaller feature set. Note that in a very limited number of experiments where the arm was moving in one plane (for example one of the X, Y and Z coordinates did not change at all), the correlation between at least one coordinate and ECoG signals was poor. Although, in this case one may be tempted to remove the coordinate that has poor correlation to ECoG signals, it is our opinion that these particular cases actually help the classifier identify them.

2.7.4 Effects of the type of ECoG signals. We compared the effect of using monopolar (MP) ECoG signals against differential ECoG signals (DA and DN) electrodes. This allowed us to determine if using monopolar signals or differential signals (representing differences between different monopolar signals) had any impact on the performance of the classifier.

2.7.5 Effects of histogram bin width. We also explored the effect of using bins representing different bandwidths to generate the histograms. This gave us an opportunity to determine if the performance of the classifier was dependent on the bandwidth used to group spectral components.

3. Results

3.1 Correlation between ECoG spectral components and kinematic recordings

The correlation coefficients between the kinematic recorings and ECoG spectral components used were in the range of 0.15 ± 0.006 to 0.63 ± 0.01 (mean $\pm$ SD). These values were obtained averaging all of the available trials, movements and subjects. Figure 5 shows an example of three spectral components with the highest correlation coefficients against position recordings (X,Y,Z) for a single RTR trial.

3.2 Representation of correlated frequency components using histograms

The histograms revealed consistent and unique distributions that were representative of the individual upper limb movements. As shown in figures 6 and 7, each one of the movements generated a unique histogram for each of the kinematic dimensions. The histograms were also subject specific (i.e., histograms corresponding to the same movement were different for both subjects).

3.3. Classification tests

3.3.1 Effect of the number of trials used to create the training vectors for the classifier. The classification accuracy was highly dependent on the number of trials used for the classifier ($p < 0.0001$), as can be seen in figure 8. The lowest accuracies were obtained when using a single trial to train the classifier, while using 5 trials to generate the training feature vectors for the classifier yielded the highest accuracies.

3.3.2 *Effect of the number of frequency components used to create the training vectors for the classifier.* The number of spectral components used to create feature vectors to train the classifier had a positive effect on the classification accuracy, as shown in figure 9, up to 20 spectral components. Increasing the number of spectral components used to train the classifier beyond 20 did not improve the classification accuracy, as confirmed by the multiple comparison test. This was tested for various ECoG signals namely monopolar, differential adjacent, differential nonadjacent, and combination of monopolar and differential adjacent signals.

3.3.3 Effects on the kinematic dimensions used. There was no significant difference in classification accuracy as a result of using only X, Y and Z kinematic data versus all kinematic data, i.e., X, Y, Z, roll, yaw and pitch, to perform the classification ($p<0.01$). The averages were estimated over all number of trials to train the classifier (1 to 5) and all number of spectral components tested (5 to 40).

3.3.4 Effects on the type of ECoG. The accuracies obtained using monopolar, differential adjacent, differential nonadjacent, and combined monopolar AND differential adjacent AND differential nonadjacent signals were different ($p < 0.0001$) (see figures 8 and 9). The accuracies achieved using differential adjacent and differential nonadjacent signals were significantly greater than those achieved using monopolar signals. The difference between the accuracy obtained using differential adjacent and differential nonadjacent was not significant by the multiple comparison test. The best accuracies were obtained using four or five trials to create the training vectors using differential nonadjacent differential signals.

3.3.5 Effect on the size of the frequency bins used for the generation of the histogram. The size of the frequency bins used to create the histograms was found to have a positive effect on the classification accuracy, as can be seen in figure 10. The highest accuracies were obtained using frequency bins of 10 Hz and differential nonadjacent and differential adjacent signals (84.4% and 81.2%, respectively). Using a frequency bin of 3 Hz resulted in the lowest accuracies. The multiple comparison test showed all of the accuracies obtained with different frequency bins to be significantly different except for frequency bins of 7 and 10 Hz.

3.4 Summary

Significant correlations were found between the spectral changes of ECoG signals and kinematic recordings. The frequencies significantly correlated with movement forming consistent and unique distributions when grouped in a histogram, making it possible to classify specific movements. The classification accuracy was dependent on the number of trials and number of spectral components to create the classifier. The performance of the classifier was also dependent on the type of ECoG signals and the size of the frequency bins used by the classifier.

4. Discussion

We presented a novel method for the identification of specific motor tasks from ECoG signals. The process described here 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. 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 was especially evident on the histograms generated while both individuals performed the same motor tasks (RTR and RTL). As expected, this finding suggests that the ECoG features that can be used for the identification of specific motor tasks are subject specific.

As expected, we showed that classification accuracy improved proportionally to the number of trials used to train the classifier. However, our results suggest that it may be possible to achieve very good recognition accuracies using only 4 or 5 trials to create feature vectors to train the classifier.

We determined that a higher number of spectral components used to create the vectors for training and classification increased the accuracy of the classifier. The classification range of values tested (5, 10,…, 40) allowed us to see a plateau in the recognition accuracy. This suggests that there is a maximum number of spectral components that can be used to train the classifier after which no significant improvements in recognition can be achieved. In our results, the recognition accuracy reached a maximum value after approximately 20 spectral components.

The spectral components correlated with the different kinematic components of each movement were grouped in histograms with bins of 3 Hz, 5 Hz, 7 Hz and 10 Hz. We observed a proportional increase of classification accuracy, with the highest values obtained for the frequency bins of 10 Hz. The accuracy was not affected by the kinematic recordings used to conduct our classification tests.

Our results demonstrate that it is possible to use signals obtained with subdural electrodes with only four contacts placed over the motor cortex to classify movements performed by an individual. We were able to determine that using differential signals representing differences between monopolar signals greatly increases the performance of the classifier as compared to monopolar signals. This is likely because a large component of the monopolar signal is related to activities of the reference electrode rather than activities of the motor cortex. In addition, the accuracy among the differential signals was greater when differential nonadjacent signals were used. This may be due to the fact that differential nonadjacent signals conveyed information over a larger area of the motor cortex as compared to differential adjacent signals.

One advantage of using subdural electrodes in the context of brain-computer interfacing over systems that use scalp electrodes is an increased ability to record activity above 30 Hz. From the work presented here it was evident that frequencies greater than 40 Hz played an important role in the identification of the individual motor tasks. This is consistent with results obtained by others [19, 21, 33, 36, 38, 55, 56]. In particular, there is mounting evidence that ECoG signals with frequencies between 100 and 200Hz may contain useful information pertaining to BCI applications [19, 21]. Technical limitations of the equipment used in our study did not allow us to acquire the ECoG signals at a higher rate than 200 Hz (traditional in clinical settings) and explore frequencies greater than 100 Hz.

The fact that the participants of the study were not part of the target population of BCI technology may raise the question of whether or not the work presented here would be applicable to the targeted patient population. The method presented here is based on establishing similarities, estimated by a correlation coefficient, between changes in power of frequency bands of ECoG signals and kinematic recordings. It has been reported that in subjects with Parkinson's Disease, changes in power in the 8-12Hz band begin closer to the onset of hand movements when compared to control subjects [57]. Although it is unknown what specific effect this would have on the performance of the procedure presented here, there is the possibility that this difference in the temporal evolution of spectral changes, as related to voluntary movement, might affect the correlation values on which the presented method is based. This might require modifications to the feature extraction process yet we feel confident that this classification method would work with diverse patient populations. In this particular study we had two patients with different diagnoses, namely Parkinson's Disease and Essential Tremor, and the proposed clasification method worked well with both individuals and achieved identical clasification accuracy.

To achieve the highest classification accuracy with the proposed BCI method one should use 10 Hz bins, five trials for training, and differential adjacent or differential nonadjacent ECoG signals. If these conditions are satisfied one should expect to have classification accuracies of 89 % or higher. It is worth mentioning that this method requires a very low number of training trials (maximum five) to generate the classifier with such high classification accuracy. Furthermore, the method of classification, namely nearest neighbour classifier, is transparent, easy to implement and intuitive. The only deficiency of this method is that it requires an individual to complete the kinematic task before the classification can be carried out. Our immediate future work will be focused on developing a classifier that will be able to perform the classification while the task is being executed. Our long-term goal is to apply this classification method to imagined movements. If successful, either of these two approaches will allow us to apply this classifier in real-time BCI applications.

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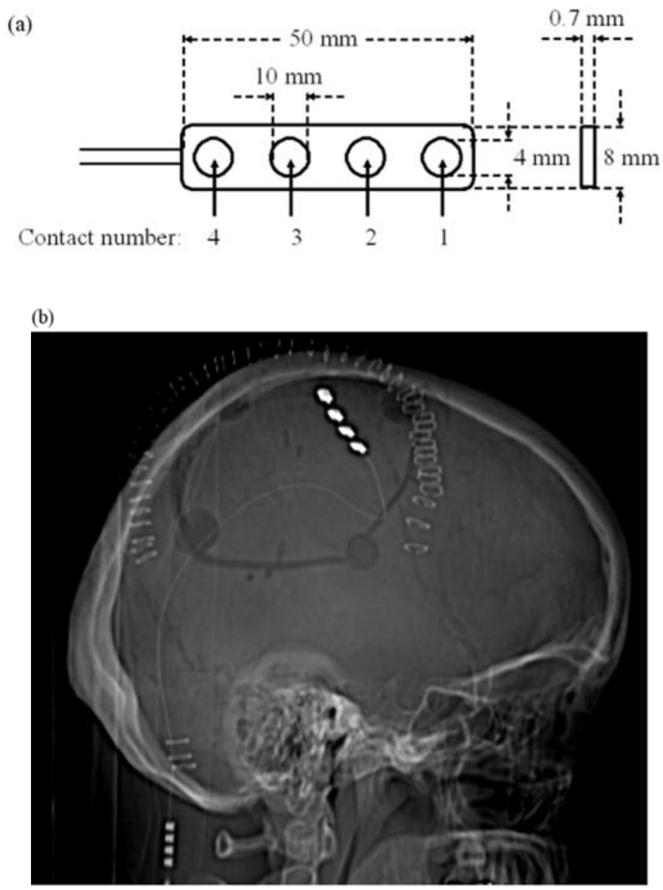

Figure 1. (a) Physical characteristics of the subdural electrodes used in this study. Both subjects were implanted with subdural electrodes over the motor cortex. The contacts were made of platinum embedded in a silicone sheet to provide structural support. (b) X-ray image showing the implanted subdural electrodes for subject 2.

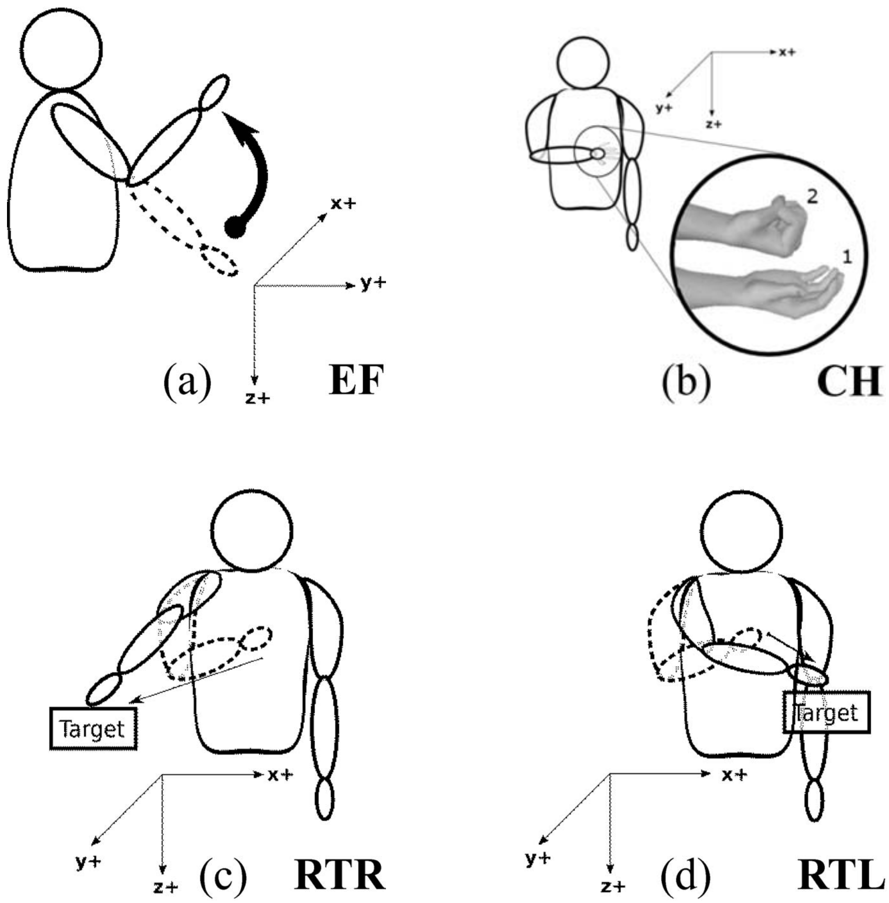

Figure 2. Movements performed by the participants of the study: (a) elbow flexion (EF), (b) closing hand (CH), (c) reaching to a target placed 30 cm to the right of the individual's midline (RTR), and (d) reaching to a target placed 30 cm to the left of the individual's midline (RTL). Subject 1 performed tasks EF, RTR, and RTL. Subject 2 performed tasks CH, RTR and RTL.

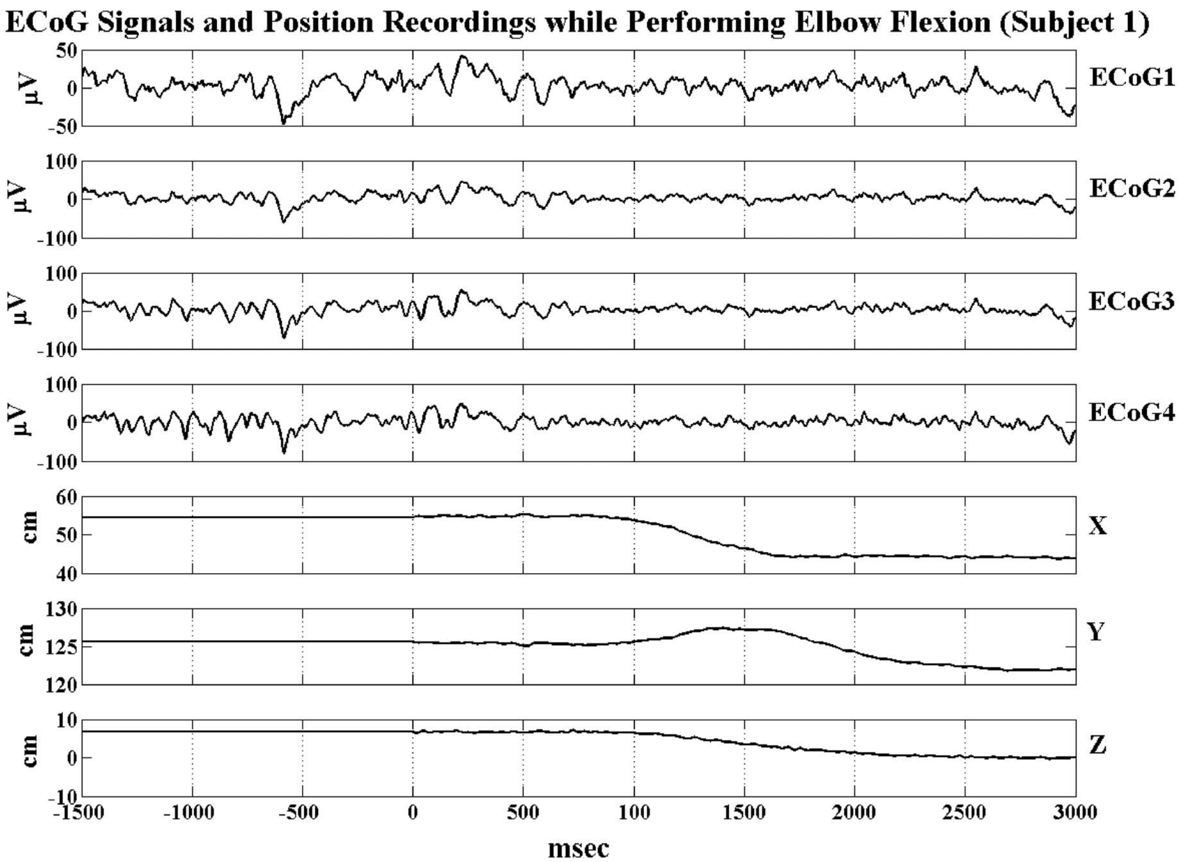

Figure 3. Example of the data recorded in our experiments. The onset of movement (t=0 sec) was defined as the moment in which the magnitude of the movement reached 5 % of its total amplitude.

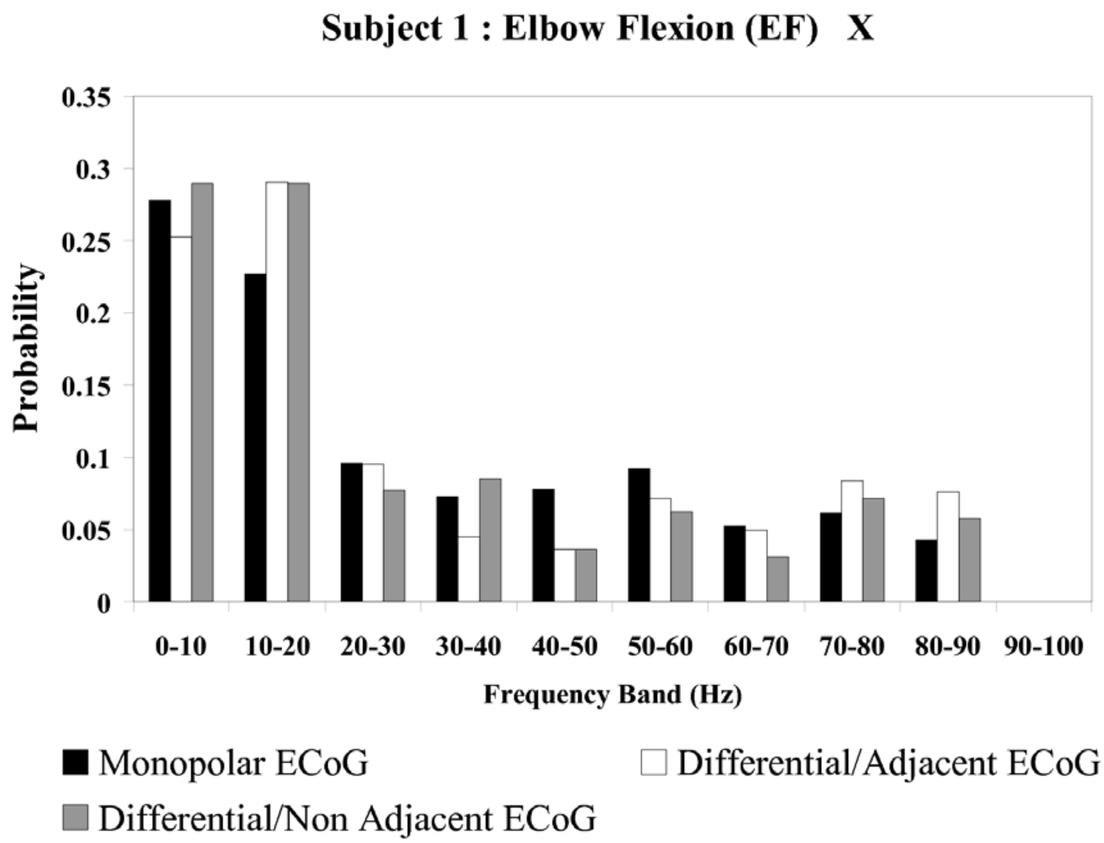

Figure 4. Distribution of ECoG frequency components correlated with the X-coordinate while subject 1 was performing elbow flexion (EF). The magnitude of each bin in the histogram indicates the probability that the frequency it represents is correlated with the kinematic dimension. The probabilities of each ECoG signal for each configuration tested (MP, DA, and DN) signal combinations have been averaged.

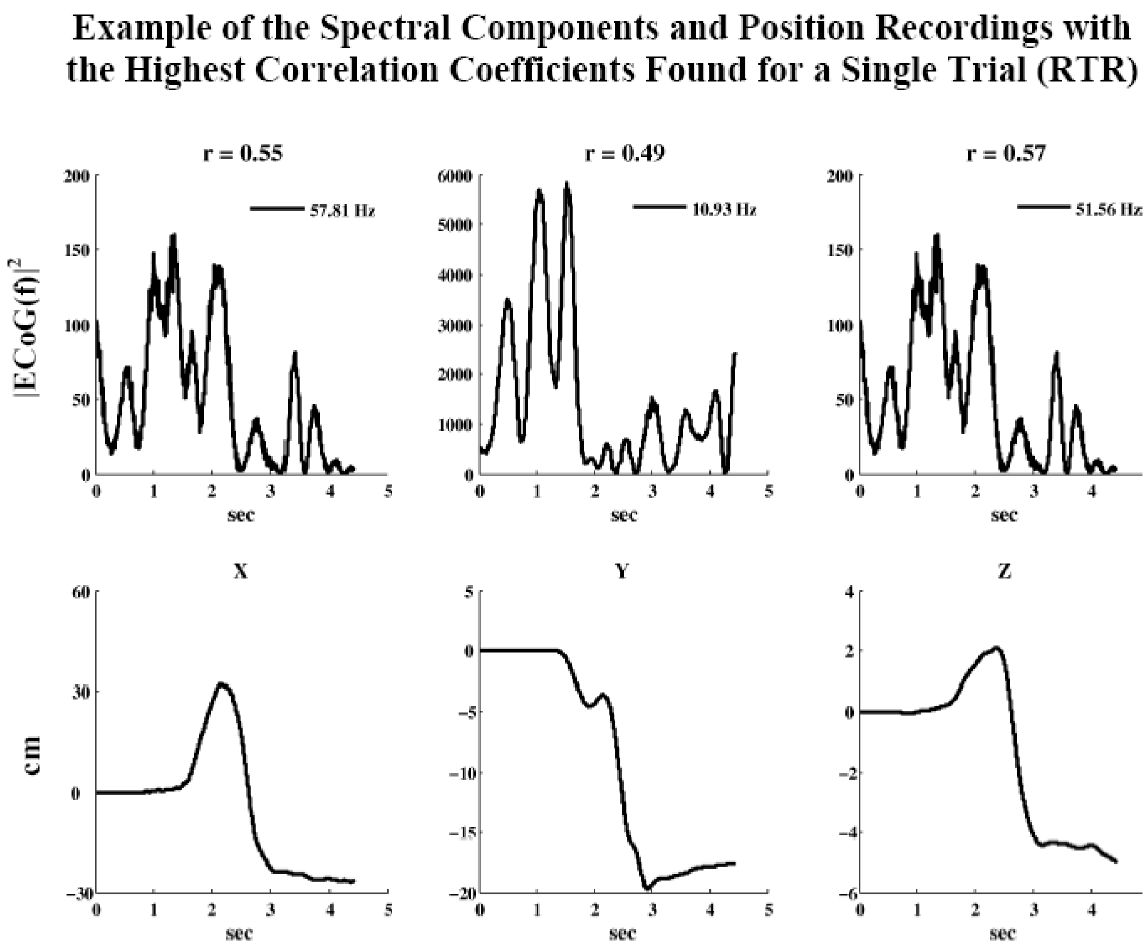

Figure 5. Example of correlated spectral components and kinematic recordings. The spectral components shown were found to have the highest correlation coefficients for a single trial (reaching to the right - RTR). Consistent with observations in the time domain, the spectral component (10.93 Hz) correlated with the Y component of movement contains more power than the other to shown spectra (57.81 Hz and 51.56 Hz).

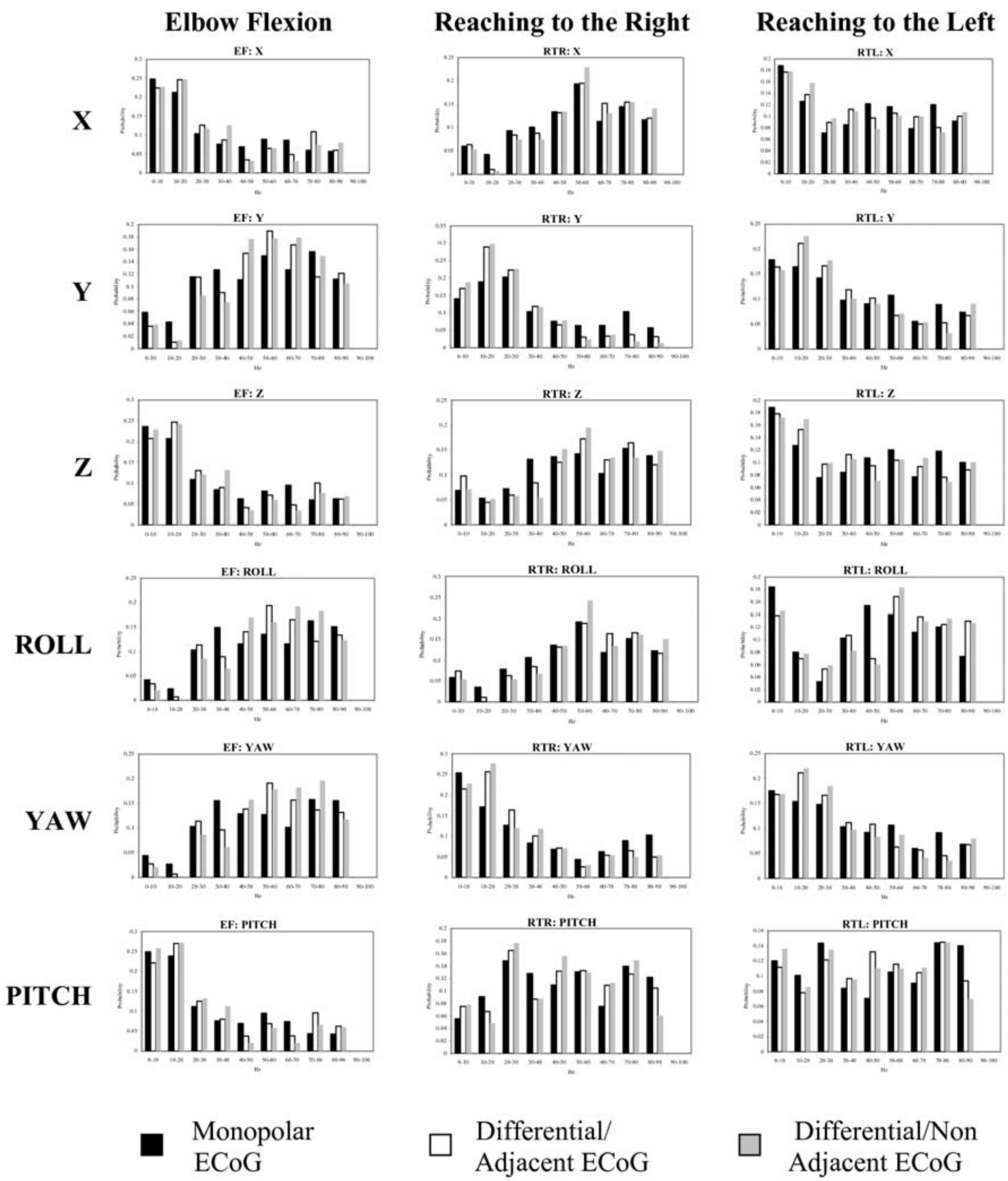

Figure 6. Histograms obtained using frequency bins of 10 Hz for Subject 1. Each one of the movements generated a different histogram for each one of the coordinates.

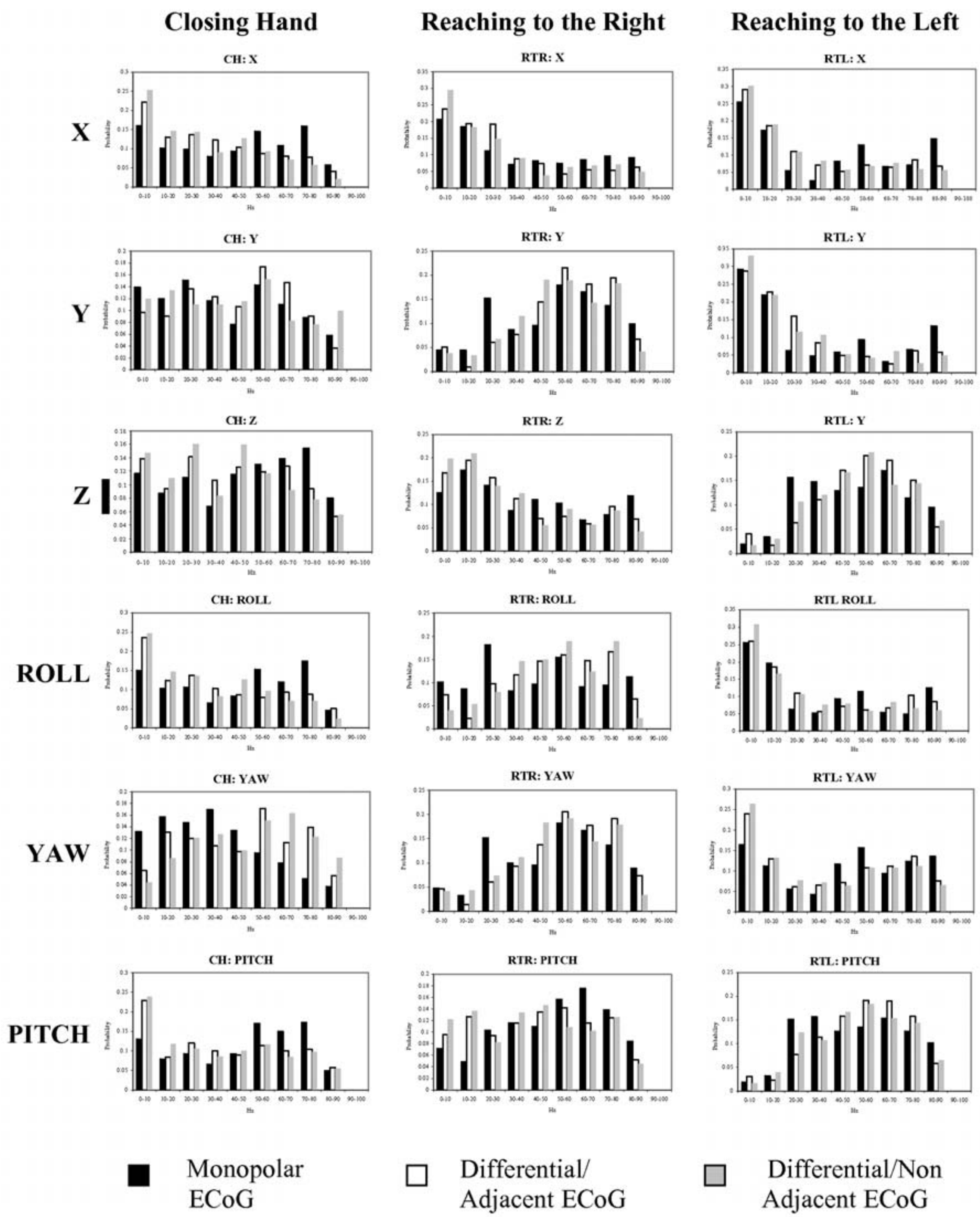

Figure 7. Histograms obtained using frequency bins of 10 Hz for Subject 2. Each movement generated a different histogram for each one of the coordinates.

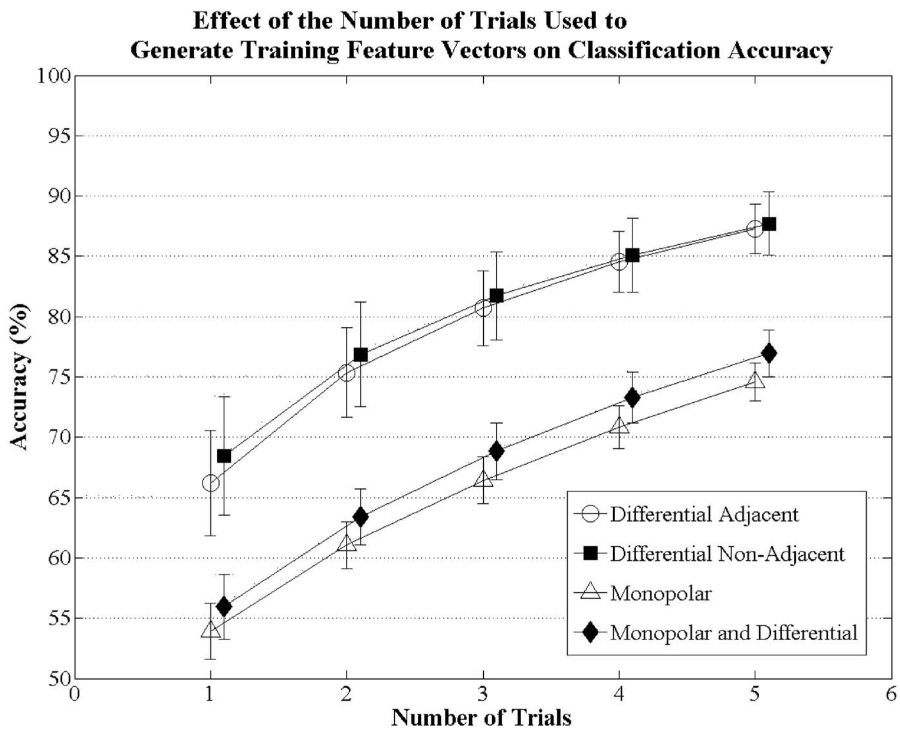

Figure 8. Classification accuracy obtained with different number of trials used to create the feature vectors used to train the classifier. The graph was generated using all of the frequency bin widths (3 Hz, 5 Hz, 7 Hz and 10 Hz) to group the spectral components in the histogram and all kinematic information (X, Y, Z, roll, yaw and pitch). The values shown represent the accuracies obtained averaged across all of the frequency components (5, 10, …, 40). The classification accuracy was highly dependent on the number of trials used for the classifier ($p < 0.001$). The difference in classification accuracy between using four and five trials to train the classifier was found to be insignificant by the multiple comparison test. Accuracy prediction using a quadratic model of the data revealed that accuracy did not improve significantly beyond 5 trials.

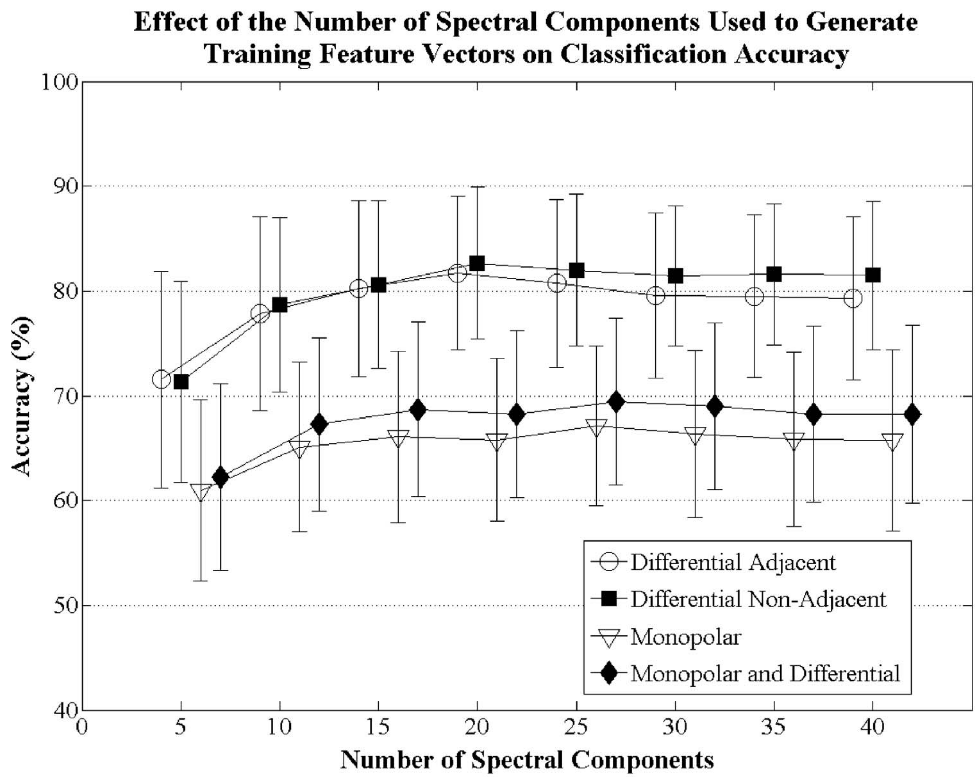

Figure 9. Classification accuracy obtained with different number of spectral components to create the feature vectors to train the classifier. The graph was generated using 5 Hz and 10 Hz frequency bins to group the spectral components in the histogram and all kinematic information (X, Y, Z, roll, yaw and pitch). The values shown represent the accuracies obtained averaged across all of the number of trials tested (1 through 5). The number of spectral components used to create training vectors to train the classifier had a positive effect on the classification accuracy. For all of the cases (DA, DN, MP, and MP & DA) the differences in accuracy were not significant when 20 or more spectral components were used to train the classifier, which was confirmed by the multiple comparison test.

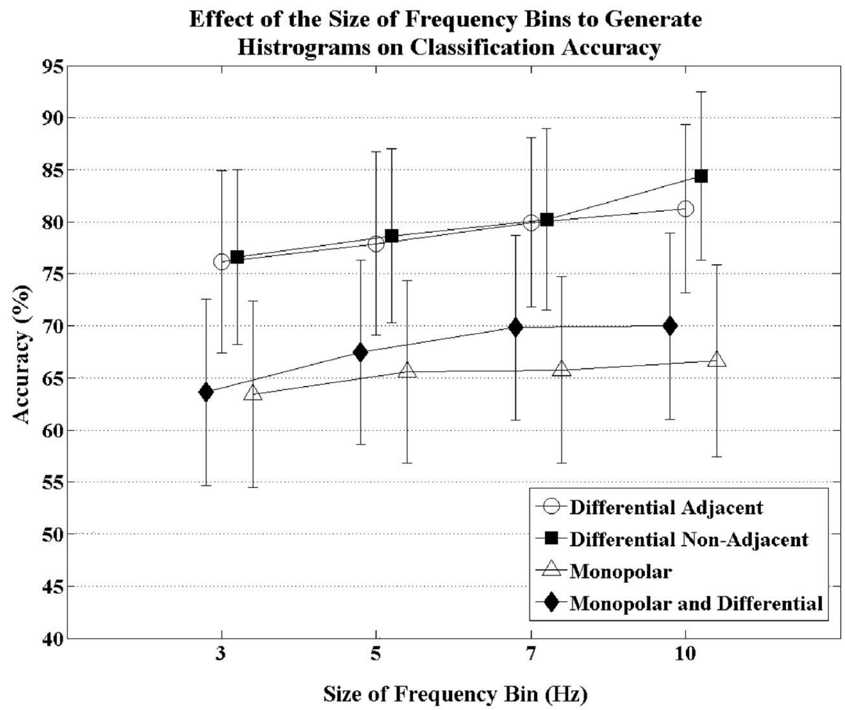

Figure 10. Effect of the size of the frequency bins used to group spectral components on the classification accuracy. The size of the frequency bins used to create the histograms was found to have a positive effect on the classification accuracy. The multiple comparison test showed all of the accuracies obtained with different frequency bins to be significantly different.