

Prediction of Five-Class Finger Flexion Using ECoG Signals

Ayman Elghrabawy, Manal Abdel Wahed

Systems and Biomedical Engineering Dept.

Faculty of Engineering – Cairo University

Giza, Egypt

aaaeg@hotmail.com – manal.wahed@eng.cu.edu.eg

Abstract— Brain Computer Interface (BCI) is one of the clinical applications that might restore communication to people with severe motor disabilities. Recording and analysis of electrophysiological brain signals is the base of BCI research and development. Electrocorticography (ECoG) is an invasive record to brain signals from electrode grids on the surface of the brain. ECoG signal makes possible localization of the source of neural signals with respect to certain brain functions due to its high spatial resolution. This study is a step towards exploring the usability of ECoG signals as a BCI input technique and a multidimensional BCI control. Signal processing and classification were validated to predict kinematic parameters for five-class finger flexion. The signal is provided by ECoG dataset from BCI competition IV. For features extraction we used shift invariant wavelet decomposition and multi-taper frequency spectrum. Multilayer perceptron and pace regression were used for classification. Results show that the predicted finger movement is highly correlated with movement states.

Index Terms— BCI, ECoG, finger flexion, shift invariant wavelet decomposition.

I. INTRODUCTION

Brain Computer Interface (BCI) is a method of communication based on neural activity generated by the brain and is independent of its normal output pathways of peripheral nerves and muscles [1]. It can provide control of prosthetic, electronic, or communication devices via direct use of the individual's brain signal. Such interface can be considered as being the only way of communication for people affected by a number of motor disabilities or suffer from locked-in syndrome in which a patient is aware and awake but cannot move or communicate verbally due to complete paralysis of nearly all voluntary muscles in the body except for the eyes. This technology has been studied for a few decades using different methods for neural recording and signal processing [2]. One of the key factors for a successful BCI application is identifying cortical representation of movement, and several studies have previously shown that hand movement (e.g. hand positions, movement direction and speed) can be predicted from the activity of populations of motor cortical neurons [3], [4], [5].

BCI hardware can record brain signals either invasively (e.g., local field potentials (LFP), electrocorticography (ECoG), single unit activity) or non-invasively (e.g.,

electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS)). While non-invasive BCI's are convenient, safe and inexpensive, but they have relatively low spatial resolution [6]. Invasive BCI's have greater precision and sensitivity than non-invasive ones.

Electrocorticography (ECoG) is a partially invasive recording of brain signals from the cerebral cortex. ECoG has recently emerged as a promising recording technique for use in BCI [7]. ECoG has a spatial resolution of 1 cm and temporal resolution of about 5 ms, high amplitude (50-100 μ V) and low vulnerability to artifacts. ECoG has a long-term stability because it is recorded by subdural electrode arrays and does not require electrodes that penetrate into cortex [8]. The diameter of one ECoG electrode is of 4 mm with 1 cm inter-electrode distance. The fine spatial resolution of ECoG can lead to direct neural interfaces implementation [9].

Since its development in the 1950's, ECoG has been used to localize epileptogenic zones during presurgical planning, map out cortical functions, and to predict the success of epileptic surgical resectioning. Previous studies have analyzed ECoG activity for BCI purposes. Lal et al. [7] used ECoG data to classify imagined movements from tongue and hand. Eric C. Leuthardt et al. [8] demonstrated the ability to use ECoG activity associated with imagery to control a one dimensional computer cursor rapidly and accurately. Fingers movements' action starts from pyramidal and non pyramidal cells in motor cortex. Pyramidal cells as the major output neurons send long axons down the spinal cord. Primary motor cortex neurons fire 5-100 msec before the onset of a movement [10]. Finger movement has three states (Extension, Flexion and Idle) [11]. Kubanek et al. [12] showed that ECoG signals can be used to accurately decode the time course of the flexion of individual fingers in humans. Wang et al. [13] proposed the use of a sparse Gaussian process with pseudo-input for decoding finger flexion from ECoG signals; they improved their work by using switching non-parametric dynamic systems [14]. Laurent Bougrain and Nanyang Liang [15], [16] decoded finger flexion from ECoG signal by using amplitude modulation and band specific features. Flamary and Rakotomamny [17] presented another approach based on switching linear models. Samiee et al. [18] presented different algorithms for classifying five-class finger flexion from ECoG signals (Fisher Linear Discriminate

(FLD), Support Vector Machine (SVM), and K Nearest Neighbour); they used Principle Component Analysis for feature extraction and Scatter Matrix for feature selection. Ibrahim Onaran et al. [19] decoded the movement and resting states of individual fingers from multichannel ECoG recordings, they developed a new hybrid decoding system based on the fusion of SVM and Hidden Markov Model (HMM) structures.

Most of the ECoG studies didn't reach to a high accuracy of signal prediction and therefore couldn't help explain fingers behaviors. In this study we investigate the prediction of the kinematic parameters of individual fingers from ECoG signals. Dataset 4 in BCI competition IV 2008 [20] was used. The dataset contains brain signals from three subjects as well as the time courses of the flexion of each of five fingers; next section presents the description of this dataset. Competitor's submissions were evaluated with respect to the average correlation between actual and predicted finger flexion. Our approach is explained in the next section.

II. METHODOLOGY

A. Dataset Description

The fourth dataset from BCI competition IV contains ECoG signal and finger flexion time courses for three subjects. The subjects were three epileptic patients who had platinum electrode grids placed on the surface of their brains. The electrodes were configured in 8x6 or 8x8 arrangements, the exact location of the electrodes was unknown, the electrodes had a diameter of 4 mm and the inter-electrode distance was 1 cm.

ECoG signals of the subject were recorded at a 1 KHz sampling using the general purpose BCI system BCI2000 [21]. A band-pass filter from 0.15 to 200 Hz was also applied. The finger movements were recorded using a dataglove sampled at 25 Hz. The subjects were cued to flex a particular finger by the corresponding word displaying on a computer monitor placed at the bed side. The dataset consists in a 10 minutes recording per subject. There were 30 movement stimuli for each finger for each subject. Each movement lasted two seconds followed by a two-second rest period. During the movement period, the subject moved the requested finger 3-5 times. The first 6 minutes 40 seconds recordings were given for training, while the last 3 minutes 20 seconds recordings were used for testing purposes. Dataset and detailed description can be downloaded from the official website of the BCI Competition IV [20], [22].

B. Data pre-processing

Data size was reduced to half by down sampling from 1 KHz to 500 Hz for all the channels. As confirmed by [12], ECoG activity most useful information is in the high frequency bands (from about 70 Hz to about 200 Hz), down sampling more than half will cause aliasing and unstable results. Undesired artifacts were removed by using FIR sharp edge band pass filter (7-175 Hz) for every channel. The range from 175 to 200 Hz is not significant in this study. Then a common reference average spatial filter was applied.

C. Shift Invariant Wavelet Decomposition tree

Discrete Wavelet Transformation (DWT) is gaining importance as feature extraction method and a classification tool because of its ability to localize structure in enhanced resolution especially in medical images. Although the DWT has many beneficial qualities, the DWT is shift-variant [23]. The shift-invariant DWT (SIDWT) algorithm [24] utilizes orthogonal wavelets, thereby resulting in less redundancy in the representation and less resource consuming. In SIDWT, the approximation coefficients and detail coefficients at each level are the same length as the original signal. The Filter Banks method, used in this algorithm, takes an input sequence and split it into subsequences using banks of filters. Farras filters [25] are used in implementation for first stage analysis and decomposition of wavelet tree. Kingsbury Q-filters [26] are used for rest of tree levels analysis. Figure 1 shows the two stage analysis filter bank; we used the waveslim software package [27] to implement the filter bank.

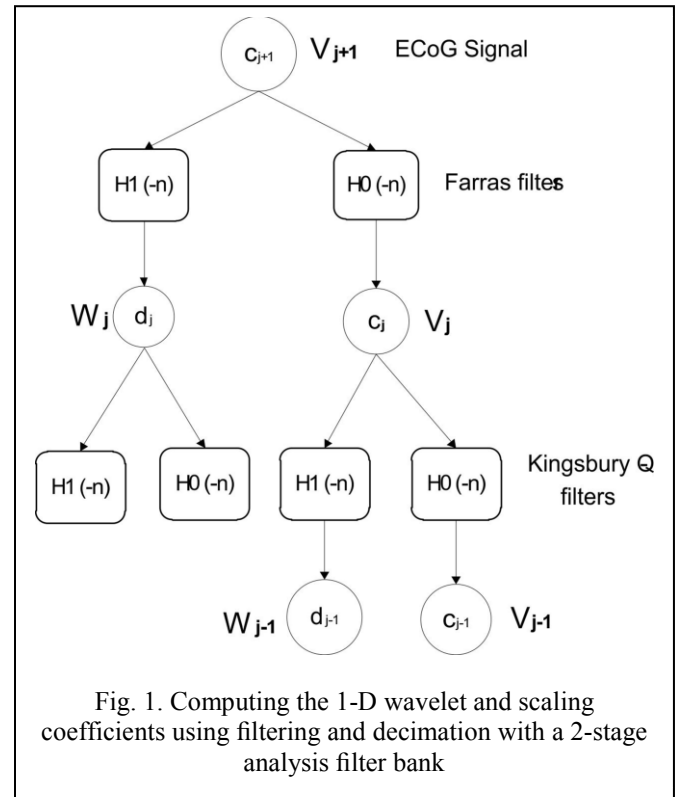


Fig. 1. Computing the 1-D wavelet and scaling coefficients using filtering and decimation with a 2-stage analysis filter bank

Wavelets can be expressed as a weighted sum of shifted scaling functions as:

$$c_j(k) = \sum_m H0(m - 2k)c_{j+1}(m), \quad (1)$$

And

$$d_j(k) = \sum_m H1(m - 2k)c_{j+1}(m), \quad (2)$$

Figure 1 illustrates that j is number of level and $c_j(k)$ and $d_j(k)$ can be found by filtering $c_{j+1}(k)$ with H_0 and H_1 , respectively, followed by a decimation by a factor of 2. The two filters, $H_0(n)$ and $H_1(n)$ are half-band lowpass and highpass filters, respectively. Consequently, the lowpass filter $H_0(n)$ produces lowpassed or averaged coefficients $c_j(k)$ and the highpass filter $H_1(n)$ creates highpassed or detail coefficients $d_j(k)$. To compute the DWT coefficients for two levels, examine the two stage analysis filterbank. By extracting dual tree up to n levels we get 2^{n-1} nodes, and a result of 2^{n-1} subsequences. These subsequences are used to extract two types of features: Spatial features (F_{Spatial}) by multitaper power spectrum approach [28], and Temporal features (F_{Temporal}) by amplitude modulation approach [15]. Both types are added to form the total set of features (F_{tot}). It is to be noted that we have removed all zero value features from F_{tot} and normalized the rest in the range 0-1 before classification. We used Chronux open-source software package for the multitaper power spectrum analysis [29].

D. Classification

Finger movement has 3 states: Extension, Flexion, and Idle. Extension is the movement of finger away from rest position, Flexion is the movement of finger towards rest position, Idle is the rest position and identified by muscle signal less than zero. In this study, two different kinematic finger models are considered. The first model classifies active (Extension or Flexion) and Idle states. The second model classifies Extension, Flexion, and Idle states. Two main classifiers have been used in this work, namely, multilayer perceptron [30] and pace regression [31]. Both classifiers are provided by weka java software [32].

Multilayer perceptron classifier (MLP) was applied to the first model. The resulting number of features F_{tot} is a huge number, thus features reduction/selection of F_{tot} is important step before MLP. Gram-Schmidt forward selection orthogonalization embedded method technique [33] was utilized for feature selection.

Pace Regression is a method of linear regression that addresses many drawbacks of standard regression, particularly the subset selection problem [31]. It overcomes the dimensionality reduction problem of input features F_{tot} , hence reduces the classification time and data over fitting. Pace Regression classifier was applied to the second model.

III. RESULTS AND DISCUSSION

By extracting the SIDWT tree up to 5 levels we get 16 nodes and a result of 16 subsequences. Then for 62 channels, $F_{\text{Spatial}} = F_{\text{Temporal}} = 992$, after removing all zero value features; $F_{\text{Spatial}} = 868$ and $F_{\text{Temporal}} = 921$, thus $F_{\text{tot}} = 1789$ feature.

After utilization of Gram-Schmidt reduction/selection technique, the number of input features to MLP became 200 features. Backpropagation multilayer perceptron with 100 hidden layer nodes was applied to the first model, Table 1 shows the results. The average of correct prediction for this model is 84.6%.

The results of model 1 indicate that the first subject ring finger has low classification value, which means that he could

not hold his ring finger alone during this time. Because the ring finger does not have an independent extensor muscle it must flex along with the little finger, this is common in majority of humans [34]. Although each subject should flex one finger at a time, ring finger has involuntary movement, it is flexing when the subject intends to flex the little finger. Figure 1 shows involuntary movement of ring and index fingers with voluntary movement of little finger which may lead to misclassification results. After removing the results of the ring finger the average of correct prediction for model 1 is 88%. When we repeated the previous approach with $F_{\text{tot}} = F_{\text{Spatial}} = 868$ the result was 78%, and with $F_{\text{tot}} = F_{\text{Temporal}} = 921$ the result was 40%. The result of the first model shows that motor movements can be classified with high accuracy.

TABLE I. FINGERS ENCODING PERCENTAGE OF CORRECT PREDICTIONS FOR 3 SUBJECTS USING SIDWT, MULTITAPER POWERSPECTRUM AND MULTI LAYER PERCEPTRON OF KINEMATIC MODEL 1 (ACTIVE AND IDLE)

Subject	Finger	Training	Testing
Subject 1	Thumb	92.2	86.0
	Index	92.3	80.0
	Middle	92.8	92.0
	Ring	93.0	40.0
	Little	92.5	94.0
Subject 2	Thumb	93.0	91.0
	Index	94.0	82.0
	Middle	93.0	98.0
	Ring	94.0	82.0
	Little	96.0	96.0
Subject 3	Thumb	95.0	85.0
	Index	85.0	91.0
	Middle	88.0	73.0
	Ring	94.0	91.0
	Little	93.0	88.0

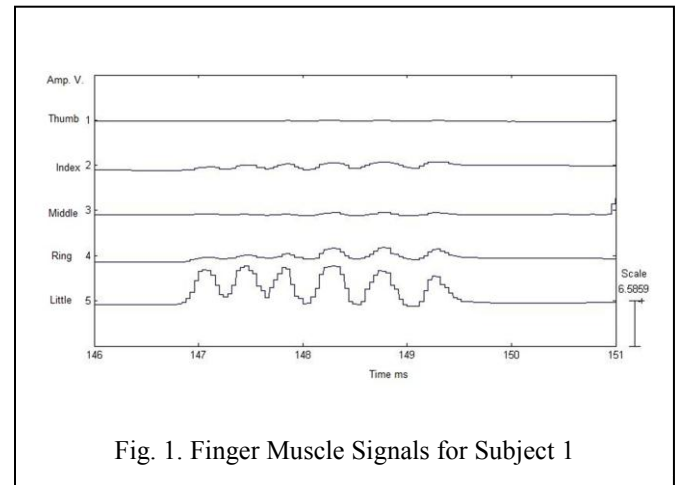


Fig. 1. Finger Muscle Signals for Subject 1

Table 2 shows the results of applying the pace regression classifier on the second model. After removing the results of the ring finger the average of correct prediction for model 2 is 13.7%. The competition contributor results were 46% (winner), 42% (2nd place), 27% (3rd place), and 10% (4th place). Our approach achieved a result higher than the 4th contributor, this result is satisfactory for a preliminary study, and further work has to be done to enhance the results. Taking into account the features correlation or interaction, using techniques to reduce the dimensionality such as Principal Component Analysis (PCA) in feature selection may produce an optimal collection of features that could improve the results.

The failure of the second model is mostly related to a combined transductive learning problem, domain adaption and covariate shift [35]. There are many tasks and signals extracted from different domains as:

$$P(Y_{source} | X_{source}) \neq P(Y_{target} | X_{target}) \quad (3)$$

And

$$P(X_{source}) \neq P(X_{target}) \quad (4)$$

Where muscle finger features (X) and labels (Y) both have different distribution in training (source) and testing (target) datasets.

TABLE II. FINGERS ENCODING PERCENTAGE OF CORRECT PREDICTIONS FOR 3 SUBJECTS USING SIDWT, MULTITAPPER POWERSPECTRUM WITH PACE REGRESSION OF KINEMATIC MODEL 2 (FLEXION, EXTENSION AND IDLE)

Subject	Finger	Training	Testing
Subject 1	Thumb	80.4	32.0
	Index	98.3	3.0
	Middle	92.8	21.0
	Ring	81.5	5
	Little	89.0	6
Subject 2	Thumb	90.2	7.0
	Index	54.0	5.0
	Middle	88.0	5.0
	Ring	61.8	4.0
	Little	79.2	36.0
Subject 3	Thumb	80.0	7.0
	Index	84.0	21.0
	Middle	87.5	17.2
	Ring	62.9	4.0
	Little	68.1	4.0

IV. CONCLUSION

Determining the relationship between ECoG signals and finger flexion provides new neuroscientific understanding, and may lead to improved BCI system. This paper presented an approach for decoding finger flexion using wavelet and power spectrum. It reached the level of robustness and ability to predict which finger has active and idle states, the approach results verified the anatomical fact of the ring finger. More study can be still in the road to solve labels and instances adaptation problem, adding more kinematic parameters (i.e speed with 3D direction) and extracting few features to simplify the calculation. There is still missing information to detect which hand belongs to flexion, the effect of finger

movement speed or direction and which part of the finger is moving. Classification between voluntary and involuntary movement epochs of ring finger is to be investigated.

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