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Single-trial EEG Discrimination between Wrist and Finger Movement Imagery and Execution in a Sensorimotor BCI

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***Abstract*—A brain-computer interface (BCI) may be used to control a prosthetic or orthotic hand using neural activity from the brain. The core of this sensorimotor BCI lies in the interpretation of the neural information extracted from electroencephalogram (EEG). It is desired to improve on the interpretation of EEG to allow people with neuromuscular disorders to perform daily activities. This paper investigates the possibility of discriminating between the EEG associated with wrist and finger movements. The EEG was recorded from test subjects as they executed and imagined five essential hand movements using both hands. Independent component analysis (ICA) and time-frequency techniques were used to extract spectral features based on event-related (de)synchronisation (ERD/ERS), while the Bhattacharyya distance (BD) was used for feature reduction. Mahalanobis distance (MD) clustering and artificial neural networks (ANN) were used as classifiers and obtained average accuracies of 65 % and 71 % respectively. This shows that EEG discrimination between wrist and finger movements is possible. The research introduces a new combination of motor tasks to BCI research.**

***Index Terms* — Brain-computer Interface (BCI), electroencephalogram (EEG), event-related (de)synchronisation (ERD/ERS), independent component analysis (ICA)**

I. Introduction

PEOPLE who suffer from motor impairments can benefit greatly from a system that can return some of the essential functionality of the human hand [1]. Such people may have had an arm amputated or have suffered a stroke or spinal cord injury [1]. The lost hand of an amputee can be replaced by a robotic prosthetic hand, while the non-functional hand of a victim of a stroke or spinal cord injury can be supported by a robotic exoskeletal orthotic hand [1]. These external devices can then be controlled using the user's thoughts with the help of a brain-computer interface (BCI) to reroute the signals directly from the brain to actuators in the prosthetic/orthotic hand [1, 2].

This solution can be used to allow motor-impaired individuals to perform essential hand movements that facilitate the performance of daily activities [1, 3]. Considering the movements that patients learn during motor rehabilitation [4, 5], five basic hand movements are considered i.e. wrist extension (WE), wrist flexion (WF), finger extension (FE), finger flexion (FF) and the tripod pinch (TR). Occupational therapists consider these to be the most essential hand movements [4, 5, 6].

The core of an effective BCI solution will require that the neural information associated with the essential hand movements be extracted and translated from neural signals, such as electroencephalogram (EEG), in real-time [7, 8]. The combination of these five essential hand movements has not yet been explored in EEG-based BCI literature [9]. It is thus necessary to first investigate the possibility of interpreting the EEG for the five hand movements offline on a single-trial basis since this serves as a first step toward real-time BCI functionality [1, 9]. BCI literature has shown that the discrimination of movements on the same limb is a challenging task [9]. However, success has been shown in the classification of binary combinations of four types of wrist movement tasks on the same hand [10, 11]. This suggests that the binary classification of other types of unilateral hand movements may be possible. To date, a study has not been conducted to differentiate between major parts of the hand i.e. the wrist and fingers [9-12]. Hence, as an intermediate step, the differentiation between EEG for wrist and finger movements is investigated in this paper by grouping WE and WF into one class and FE, FF and the TR into another. This forms part of the effort to improve on the incomplete understanding between central neural signals and hand movements [2].

II. Background

A. Electroencephalogram and ICA

There are several challenges associated with the extraction of relevent information from EEG. The signals are small (in the μV range), and present a large inter-trial variability [1].

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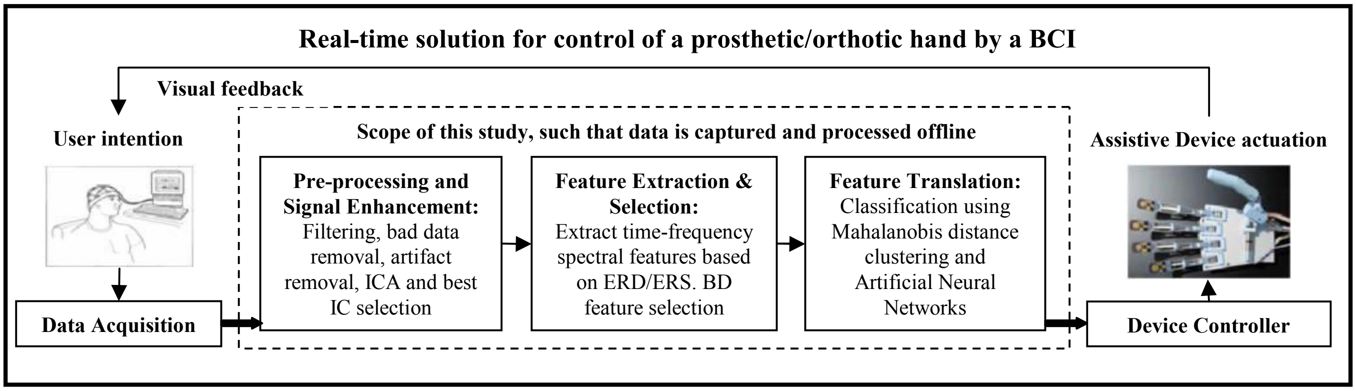

Fig. 1. Model of a sensorimotor BCI used for communication to a prosthetic hand.

Recording activity from billions of simultaneous neural processes from a limited number of EEG electrodes (e.g. 128 electrodes) results in a considerable mixing of information sources from all over the head at each electrode [1, 13]. However, clinical research has increased the understanding of EEG signals and their relationship with imagined movements and inexpensive computer equipment supports the computational demands for EEG signal processing [1, 8 14]. Hence EEG can be used as a suitable signal source for basic prosthetic/orthotic hand control [1] in a controlled laboratory environment.

ICA is commonly used in BCI research to remove artifacts, but has also proven useful in separating biologically plausible brain components whose activity patterns relate to behavioural occurrences [13]. In some studies, ICA has shown superior performance over other methods of spatial filtering [15, 16] and has aided the discrimination of EEG for different unilateral wrist movement tasks [11]. This suggests that it may be beneficial for isolating rhythmic activity from the sensorimotor cortex for other types of hand movements [1].

B. *Sensorimotor Brain-computer Interface*

The main components of a BCI are shown in Fig 1. They enable the actuation of the external device according to the user's intent [1, 17]. Sensorimotor BCIs are ideal for the control of a prosthetic/orthotic hand since they deal with motor functions from and sensory inputs to the sensorimotor cortex of the brain. Prominent electrophysiological features associated with the brain's normal motor output channels are mu (8–12 Hz) and beta (13–30 Hz) rhythms [1, 17]. The rhythms are synchronised when no sensory inputs or motor outputs are being processed [1, 17]. Movement or movement preparation results in a desynchronisation (decrease in amplitude) of the mu and beta rhythms, referred to as event-related desynchronisation (ERD) [1, 17]. Event-related synchronisation (ERS) occurs after movement when the rhythms synchronise (increase in amplitude) again [1, 17]. ERD and ERS occur during imagined movements as well, making them suitable for paralysed individuals [1, 3]. Features based on ERD/ERS have been used successfully to classify EEG for some types of wrist movements [10, 11].

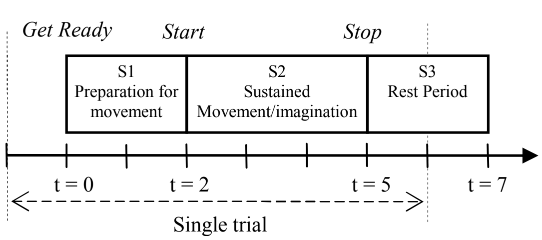

Fig 2. Time sequence and instructions for a single trial

III. Methodology

Fig 1 summarises the major processes that make up the method in order to classify between unilateral wrist and finger movements. The process is applied to real and imagined movements.

A. *Data Acquisition*

Data was captured from five right-handed, healthy, male, untrained volunteers in their early twenties. The subjects were seated in a chair, resting their forearm on an arm rest [10, 11]. A computer screen was used along with custom Eprime software [18] to queue the movements while the subjects' EEG were measured. An EGI system that consisted of 128 high-impedance scalp electrodes (forming the GSN 128) along with the Geodesic EEG System and Net Station Software was used [19]. The electrodes were Ag/Ag-Cl electrodes with sponge attachments soaked in an electrolyte solution of potassium chloride [19].

Each subject was asked to perform real and imagined sets of the 5 selected movements for each hand (starting with the right hand). Therefore, for each hand, the subjects performed 10 sets of movements: 5 for real movements and 5 for imagined movements. Each set consisted of 20 repetitions/trials of one type of movement [11]. The order of the sets was randomised and thus differed for each subject so that no movement type was preferred [12]. In summary each test subject performed: movement set (5) × L/R hand (2) × real/imagined (2) × repetitions (20) = 400 trials.

The type of movement for each set was shown to the subjects on the computer screen prior to the commencement of the set and a brief practice session was allowed. There were short breaks between sets and the repetitions for each set were performed continually. The trials were queued by instructions shown on the computer screen, the timeline of which is shown in Fig 2 [11, 20].

B. Pre-Processing

EEGLAB was used to handle the pre-processing [13]. Noisy channels were removed and a bandpass filter between 0.5 Hz and 100 Hz was applied to the data [11, 20], which was sampled at 200 Hz by the EGI system [19]. A 50 Hz notch filter was also applied [16].

Data was then divided into 7 s trials, from t = -1s to t = 6 s, placing t = 0 at the *Get Ready* event (pre-movement stimulus) shown in Fig 2. This was done so that the continuous signals were not split in the crucial areas of S1 and S2. The left hand data for subjects 1 and 4 was unusable and thus discarded.

The Automatic Artifact Removal (AAR) toolbox for EEGLAB [21] was used to remove artifacts, which included electro-oculogram from eye-blinks and eye movements, and electromyogram from tongue, face, neck and shoulder movements [1]. Artifacts were removed using spacial filtering and blind source separation [21]. A bandpass filter between 8 – 30 Hz was then applied to isolate and mu and beta data [10].

C. ICA and Source Localisation

ICA was run using the infomax algorithm on the individual hands of each subject [13]. This decomposed the EEG into separable localised sources of potentials. The potentials or ICs emanating from the motor cortex were visually selected and isolated. The criteria for selection were based on:

1. Viewing localised activity mainly in the region of the primary motor cortex that controls the hand, but activity in the supplementary motor area and premotor area was also considered [22]. 2D top-view plots of voltages across the scalp for each IC indicated the region of neural activity.
2. The presence of ERD just prior to and/or during S2 as well as ERS after S2 [23]. This was calculated using the inter-trial variance method [23].

Several ICs representing motor activity were selected per subject and per hand. This approach is advantageous since the inter-subject variability of EEG makes it difficult to predict which electrodes provide relevant information [22]. It also helps to capture the information from different regions of the motor areas, which may activate during different stages of movement [22]. Furthermore, it reduces the dimensionality of the data and filters contamination from non-sensorimotor neural potentials, such as the visual alpha rhythm [17]. The number of selected ICs varied between test subjects, ranging between 8 and 12.

D. Feature Extraction and Selection

A time-frequency technique, originally used for audio identification [24], was adapted and used to extract power spectral features from the selected ICs (since audio and EEG signals are both non-stationary). The time range from t = 1 s to t = 4 s was considered (see Fig 2) in order to include pre-movement and movement execution/imagination phases. An overlapping sliding window of 300 ms was then applied in increments of 100 ms [11, 16]. The power spectrum for each window was calculated using an FFT. The frequency spectrum was then split into 7 bands of 3 Hz each [20] and the sum of the powers within each band formed a feature. 28 time windows were extracted over the time range considered, with 7 power band features each. This was done for each IC, resulting in a total number of features ranging between 1568 and 2352.

The Bhattacharyya distance (BD) was used to select the best features according to how well each feature separated the classes [16, 20]. Hence the BD was calculated for each feature and the 18 features with the largest BD were selected. This provided low dimensionality and was found to be the optimum number of features during iterative testing.

E. Classification

A clustering classifier based on the Mahalanobis distance (MD) is simple and robust and has shown good performance in BCI research [7]. The MD measures the dissimilarity between feature vectors from different classes and can also be used to remove outliers [25]. Multilayer perceptron artificial neural networks are used widely in BCI research [7] and were used to verify and possibly improve on the MD classification results.

The squared MD d_i^2 between the i^{th} vector of dataset x and the mean of dataset y can be calculated using (1), where μ_Y is the mean of dataset y and C_Y^{-1} is the inverse covariance matrix of dataset y [26].

$$d_i^{\,2} = \left(x_i - \mu_Y\right)^T C_Y^{\,-1}\left(x_i - \mu_Y\right) \tag{1}$$

The MD was then used to calculate the distance between each trial in a given class to its own mean and to the mean of the other class [26]. If the distance between a single-trial feature vector x_i and the mean of its class μ_x was smaller than the MD between that single-trial vector and the mean of the other class, then it was concluded that x_i belongs to class x. The trial being tested was removed from the calculations of the means and covariances of the classes/clusters allowing all trials to be used for testing.

Alternatively, for classification using artificial neural networks (ANNs), the data was divided into training and testing data. The number of hidden nodes was optimized iteratively considering all subjects. Hence, MLPs each consisting of 18 input nodes, 24 hidden nodes and 1 output node are trained per subject per hand.

In clinical applications, sensitivity and specificity are often used to evaluate the accuracy of diagnostic tests [27]. They respectively describe the likelihood of true positive and true negative test results [27]. Sensitivity and specificity can be generalized to 2 class datasets, for example: wrist movements = positive test result and finger movements = negative test result. Classification accuracy was thus measured by calculating the average of the sensitivity and specificity measures (*SSA*) as shown in (2), where T and F

TABLE I
CLASSIFICATION ACCURACY (%) FOR EEG DISCRIMINATION BETWEEN WRIST AND FINGER MOVEMENTS USING MD CLASSIFIERS

	Real		Imaginary	
	RH	**LH**	**RH**	**LH**
Subject 1	68	-	61	-
Subject 2	63	84	56	54
Subject 3	62	45	69	63
Subject 4	71	-	76	-
Subject 5	49	55	81	70
Subject Average	63	61	69	62
Grand Average	65 %			

TABLE II
CLASSIFICATION ACCURACY (%) FOR EEG DISCRIMINATION BETWEEN WRIST AND FINGER MOVEMENTS USING ANN CLASSIFIERS

	Real		Imaginary	
	RH	**LH**	**RH**	**LH**
Subject 1	81	-	70	-
Subject 2	73	75	79	68
Subject 3	73	56	61	72
Subject 4	70	-	76	-
Subject 5	52	69	82	67
Subject Average	70	67	73	69
Grand Average	71 %			

respectively represent the number of correctly and falsely classified trials for each class. Subscripts W and F denote wrist and finger classes respectively.

$$SSA = \frac{1}{2}\left(\frac{T_W}{T_W + F_W} + \frac{T_F}{T_F + F_F}\right) \qquad (2)$$

IV. RESULTS AND DISCUSSION

The MD and ANN results are summarised in Table I and Table II respectively. Classification is shown per subject for real and imaginary movements. The results show reasonable classification accuracies, which are consistent across most test subjects for both hands. ANNs performed better than MD clustering. This is probably due to the ANNs managing to capture the hidden patterns amongst the features more accurately than the simple distance-based approach of the MD method.

Classification is slightly more successful for imagined movements than for real movements. This is contrary to the findings of other BCI studies [20], where classification results for real movements are superior due to real movements generating stronger motor neural activity [20]. However, some studies have shown similar results for real and imagined movements [11]. The superior results for imagined movements in this study could be due to the fact that all the test subjects were university students who were familiar with motor imagery. Consequently their concentration levels and imaginative skills may have been above average, which may have increased the classification accuracy for imagined movements [28]. The use of movements, such as WE, in everyday life made movement imagination in [10] easier for test subjects. In this study, the use of WE, WF, FE, FF and the TR in everyday life may similarly have made the motor imagery tasks easier for the test subjects, thus enhancing their sensorimotor EEG patterns, despite having no training.

The success of this research is important since it shows that the discrimination of neural signals from neighbouring areas of the motor cortex is possible using EEG. This allows the real or imagined movement of major parts of the hand i.e. the wrist and fingers, to be interpreted via EEG. The use of ICA along with high resolution EEG (128 channels) played an important role in this regard. Common hand movements such as FE and the TR [4. 5], which are novel to BCI literature, can be explored in future research involving prosthetic/orthotic hand control using a BCI [9]. Future work aims towards accurately classifying the individual five essential hand movements; first offline and thereafer in real-time.

V. CONCLUSION

This paper focuses on discriminating between unilateral wrist and finger movements in order to improve EEG interpretation to allow a sensorimotor BCI to control a prosthetic/orthotic hand. The average results for the MD and ANN classifiers are 65 % and 71 % respectively. These results show that the offline discrimination between wrist and finger movement EEG, for real and imagined movements, is possible. This is an important step towards allowing a prosthetic/orthotic hand to perform essential hand movements.

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