Comparing EEG Patterns of Actual and Imaginary Wrist Movements – A Machine Learning Approach

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Abstract

Our goal is to develop an algorithm for feature extraction and classification to be used in building brain–computer interfaces. In this paper, we present preliminary results for classifying EEG data of imaginary wrist movements . We have developed an algorithm based on the spatio-temporal features of the recorded EEG signals. We discuss the differences between the feature vectors selected for both actual and imaginary wrist movements and compare classification results.

Keywords: *EEG data, Brain–computer interfaces, Wrist movements, machine learning.*

1 Introduction

Brain–computer interfaces (BCIs) are interfaces that use real–time brain signals to generate commands to control and/or communicate with the environment. These interfaces would be particularly useful for people who for some reason have lost the ability to generate and/or control movement of some or all body parts, see [1] for a review on BCIs.

Research in developing successful brain–computer interfaces (BCIs) endeavours to improve the speed and accuracy of communication of these interfaces. This is achieved by improving the EEG signal processing techniques and selection of features that are translated into commands to control and communicate with augmentative and assistive devices [2].

There is extensive literature on studying EEG signals during real and imaginary motor tasks, see for example [3] for an algorithm for on–line EEG classification, [4] for a technique to classify imaginary right and left motor EEG and [5] for a method to control a cursor on a screen using EEG. The main aim of these studies is to develop techniques for classifying EEG signals during motor tasks which can potentially provide an alternative mode of communication to people with motor disabilities.

In this same endeavour, we propose a method which is based on the classification of brain activity associated with the user's intention to perform a motor task. It has been shown [6] that imaginary movements produce similar patterns to real movements. The algorithm we proposed for recognising actual (real) wrist movement from EEG signals [7] is unique in its classification power. It successfully classifies wrist movements in twenty different directions. In this paper, we extend the use this algorithm to classify the corresponding imaginary wrist movements, we discuss the differences between the features extracted and selected for real and imaginary movements and the corresponding classification results.

In the following section 2 we describe our proposed method, in section 3 we present and discuss preliminary results and in section 4 are our conclusions.

2 Methods

EEG data was recorded from a single subject using a $NeuroScan^{TM}Synamp$ system with 28 electrodes (ear referenced) placed on the scalp according to the modified 10–20 system.

In addition, 4 EMG channels were simultaneously recorded from selected muscles using the same equipment. Kinematic data of the wrist position was also recorded and later used to detect the onset of movement. Data was sampled at 2 KHz.

The subject was seated in an armchair with his right hand holding a joystick. The joystick can be moved freely among five positions: north (N), south (S), east (E), west (W) and a neutral (0) position in the centre, corresponding to 15° wrist radial, ulnar deviation, flexion, extension and neutral positions, respectively, making possible twenty different movement directions.

The data recorded consisted of a series of movement trials triggered by a visual cue. The visual cue was displayed on a monitor and consist of a small square initially placed at the centre position whilst the subject is holding the joystick in the neutral position (0). The square then switches to one of the possible positions (N, S, W, E) and from that new position to another and so on. The directions are randomised and no two consecutive directions are the same. The subject is asked to follow the direction triggered by the visual cue, move the joystick to the target direction as fast as possible and to hold the position until the following trigger appears. The time between two consecutive triggers was 10 seconds. Data was recorded for 15 trials.

The same set up was done for the imaginary movements except that the subject was asked to *imagine* the movement rather than actually performing it. EMG data was also recorded to ensure that the subject was not moving the wrist.

2.1 Data Preprocessing and Feature Extraction

Eye blinks and movement artifacts were removed from the data. The EEG signals were low–pass filtered at 50Hz. Epochs related to each direction were collated for analysis.

We are interested in extracting spatio–temporal characteristics of EEG during movement transition and movement planning. We initially used windowed fast Fourier transform (w-FFT). After a number of experiments, we decided to use continuous wavelet transform (CWT) due to its inherent characteristic of time–frequency localisation and its suitability for for analysing non–stationary biomedical signals [8]. The CWT is defined by equation 1.

$$W_x^{\psi}(s,\tau) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*(\frac{t-\tau}{s})dt \qquad (1)$$

where

$\psi^*(t)$ is the conjugate of the transforming function, also called the mother wavelet.

τ is the translation parameter, i.e. representing the shift in the time domain.

$s(>0)$ is the scale parameter, and is defined as proportional to $1/frequency$.

Data was split into training and testing sets. The estimated CWT according to equation (1) was then normalised w.r.t the variance of the training data set.

We are interested in alpha (8–12Hz), beta (18–24 Hz) and gamma (28–37 Hz) bands where motion related potentials (MRP's) may be present.

This work focused on the analysis of the EEG recorded from channel C3 during movement preparation phase immediately before the onset of movement for real movements and immediately after cue trigger for imaginary movements . Channel C3 records signals from the motor cortex area in the left hemisphere of the brain. The signal detected by C3 experience desynchnronisation when the right hand side exhibits some movement. We used the common average reference(CAR) signals [9] rather than the ear–referenced signal. CAR is a reference–free spatial filter and hence is not affected by complications associated with an actual physical reference. CAR has been found by [10] to maximise signal–to–noise ratio, hence improving speed and accuracy of EEG–based communication devices. CAR is also accurate for analysing small localised regions [11] which suits our purposes.

2.2 Feature Selection and Classification

In this phase, we select features to form a feature vector to be used in classification. The values of the elements of each feature vector are the values from the normalised CWT estimated for the different directions. These values are selected by sampling both the frequency and the time axes to include the alpha, beta and gamma bands at the time of movement preparation immediately before the onset of movement for real movements and immediately after cue trigger in case of imaginary movements.

To reduce the dimensionality of the problem, eliminate irrelevant or redundant features in the feature vector and suppress noise in the signal, we perform principal component analysis (PCA) on the feature vectors of the training set. PCA has been widely used in data compression due to its ability to achieve high compression rates with little degradation of the original signal, e.g.[12]. PCA suppresses noise and enjoys a high generalising ability [13] which makes it able to describe on the basis of a relatively small data set a much larger variety of data of the same nature. This last feature of PCA is crucial for the underlying application, as acquiring many EEG data sets for different subjects during different sessions requires a lot of effort and is time consuming.

Principal components (PCs) are selected corresponding to the eigen values in decreasing order of value, so that the first PC attributes to much of the variation in the data and each successive PC for a little less. If the first few PCs account for large proportion, say 90%, of the variation in the data, the feature vector dimension is then reduced. We use the reduced feature vectors averaged for each direction to represent the different directions.

Classification is based on simple comparison between the Euclidean distance between the feature vector and the representations of the different directions and a predefined threshold value θ. This approach is fast, efficient and require minimal computational power.

3 Results and Discussion

In this paper, we report on the results of experiments carried out to classify the twenty possible directions:'0N', '0E', '0W', '0S', 'N0', 'NS', 'EW','NE','ES', 'SW', 'WN' and the opposite directions: 'EW' denotes the direction from East to West, '0N' the direction from the centre to the North, etc. ....

We analysed the data using CWT for a period of 6 seconds: 3 seconds prior to the onset of movement and 3 seconds thereafter. Figure 1 shows the average CAR signal for C3 and the corresponding CWT scalogram for direction 0N. The CWTs were visibly different for the different directions and where superior to the features extracted from w–FFT in the classification stage.

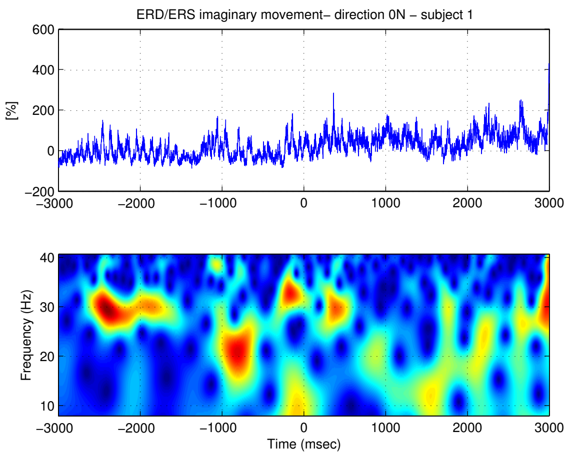

Figure 1: ERD/ERS and the corresponding CWT power spectrum of C3 in the direction 0 to North. The '0' on the time axis indicates the time of cue trigger.

We then sampled both the frequency and the time axes of the CWT scalogram to include the alpha, beta and gamma bands for 500 milliseconds prior to the onset of movement (for real movements) or 500 milliseconds after cue trigger (for imaginary movements). For each direction, a feature vector of (1×11055) was produced.

Next, we performed PCA to reduce the dimensionality of the problem by extracting a small number of PCs that account for most of the variation in the original training dataset.

Figure 2 illustrates a histogram of the eigen values produced from the PCA, showing the redundancy in the initial CWT feature vector.

We found that the first 10 PCs accounted for 96% of the variablility in the data. The feature vector dimension was hence reduced to (1×10).

For each direction, 4 samples were used for training, 2 for testing.

We experimented with different number of principal components (more than 10), threshold values θ to

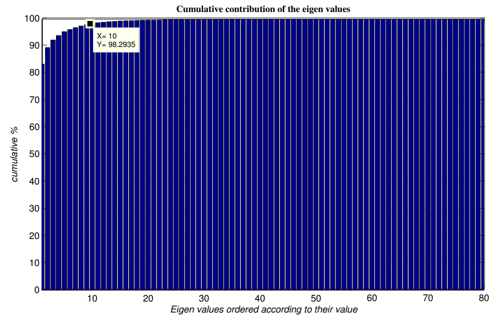

Figure 2: The estimated eigen values show the redundancy in the data set. We choose ten PCs contributing to 96% of the variation in the data.

optimise the classification results for both the training and test sets. Tables 1 and 2 show optimised classification results using 15 principal components for real and imaginary movements respectively.

Table 1: Classification Results for real movements

	Training	Testing
Recognition Rate (%)	100	87.5
Misclassification (samples)	0	4
Non-classification (samples)	0	1

Table 2: Classification Results imaginary movements

	Training	Testing
Recognition Rate (%)	67	50
Misclassification (samples)	2	7
Non-classification (samples)	3	3

The recognition rate is defined as the percentage of the number of correctly classified samples w.r.t the total number of samples in the data set. Mis–classifications are the cases where the feature vector is classified to belong to a different class (direction) and non-classifications are the cases when Euclidean distance is greater than all θ's and hence the feature vector does not belong to any class (direction).

On a closer inspection of the feature vectors for the actual movements data that were misclassified, most of them (3 out 4) were cases such as: 'E0' classified as 'EW', 'WE' classified as 'W0' and 'SN' classified as '0N'. This suggests that the features extracted cannot totally discriminate between two classes which are, in principle, defining the same direction but different in the distance travelled. This suggestion is directing us to include data segments related to movement execution when defining the feature vectors for classification in our future work.

We achieved relatively poor results for the imaginary movement data sets. We contribute that to a number of reasons amongst which that it is difficult to estimate the exact time where the subject starts to imagine the movement, so our selected feature vectors might not be accurately representing the imaginary "onset" of movement. Another factor may be that for imaginary movements, there might be a different set of neurons that are activated compared to the ones fired for actual movements.

We are also aware that the data set used for training is small, which contributes to the overall classification performance. However, the results are promising, showing that the techniques used in pre–processing the data and selecting the features are suitable and potentially useful in developing brain computer interfaces.

4 Conclusion

We presented results of work–in–progress directed at classifying wrist movements using EEG signals recorded from a subject moving a joystick. The goal is to develop a method to classify movement related potentials into the corresponding twenty different wrist movement directions. This could then be used in building a brain–computer interface to steer a wheelchair, for example. We used spatio–temporal features extracted from normalised CWT and PCA as means to represent the different directions from a training set. Classification was simply done by measuring Euclidean distance between the test samples and the representation vectors. The results are promising and show the suitability of the techniques used for this application.

We found that the method is more successful in classifying real movements than imaginary movements.

Future work will aim at improving the classification results. We shall examine including data segments related to movement execution, adding data from other EEG channels, increasing the number of trials and the number of subjects.

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