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Novel use of Empirical Mode Decomposition in single-trial classification of Motor Imagery for use in Brain-Computer Interfaces

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Abstract — **This paper presents a novel method, based on multi-channel Empirical Mode Decomposition (EMD), of classifying the electroencephalogram (EEG) recordings of imagined movement by a subject within a brain-computer interfacing (BCI) framework. EMD is a technique that divides any non-linear or non-stationary signal into groups of frequency harmonics, called Intrinsic Mode Functions (IMFs). As frequency is a key component of both IMFs and the μ rhythm (8-13 Hz brain activity generated during motor imagery), IMFs are then grouped by frequency. EMD is applied to the recordings from two electrodes for each trial and the resulting IMFs are grouped according to peak-frequency band via Hierarchical Clustering Analysis (HCA). The cluster containing the frequency band of the μ rhythm (8-13 Hz) is then selected and the sum-total of the IMFs from each electrode are summed together. A simple linear classifier is then sufficient to classify the motor-imagery with 89% sensitivity from a separate test set.**

I. Introduction

A Brain-Computer Interface (BCI) is a device that uses the brain-activity of a person as an input to select desired outputs on a computer [1]. One method of obtaining a person's brain activity as a digital input is by using passive surface electrodes and an electroencephalogram (EEG) amplifier. However as the electrodes are placed on the scalp the data suffers from a very low signal-to-noise ratio and needs to be processed before it can be correctly classified. Empirical Mode Decomposition (EMD) is a data-driven method that can be applied to any non-linear or non-stationary signal, one such application is EEG data. EMD divides the signal into groups of frequency harmonics called Intrinsic Mode Functions (IMFs) and residual noise using an iterative sifting process [2]. EMD is particularly effective with rhythmic signals due to the fact that the amplitude of IMFs must be symmetrical with respect to zero, making it ideal for application to motor imagery in BCI.

Motor imagery is a common form of BCI; it relies on the paradigm of imagined movement suppressing a rhythmic signal known as the μ rhythm in the contralateral region of a person's motor cortex, known as Event Related Desynchronization (ERD) [3]. The μ rhythm is limited to a frequency band of 8-13 Hz, with the signal predominantly occurring around 10 Hz. Simply imagining moving your left hand will suppress this signal on the right side of your motor-cortex (to the region where 'hand' is mapped) and vice versa. The signal's consistency and known parameters make it possible to isolate from the rest of the brain activity recorded in the EEG data.

As frequency is a key component of both motor imagery detection and IMFs it is logical to apply EMD to motor imagery data in order to extract rhythmic features in the form of IMFs that correspond to the frequencies of the μ rhythm. The remaining IMFs would be discarded and the IMFs relating to the μ rhythm recombined through summing to produce a filtered signal. In effect the EMD method creating a filter specific to the data for each individual.

The following section will outline the data-set used and the methodology as applied to this data.

II. Methodology

A. Data Set

The data used in this study was pre-recorded motor imagery data provided by the Graz BCI group for use in BCI Competition II, Data Set III [4]. A 25 year old female subject sat in a chair whilst an EEG recorded brain activity from electrode positions C3, Cz and C4.

As shown in Fig. 1, each trial of the motor imagery experiment consisted of a two second pause, followed by an audio cue to signify the start of the test and a fixation cross

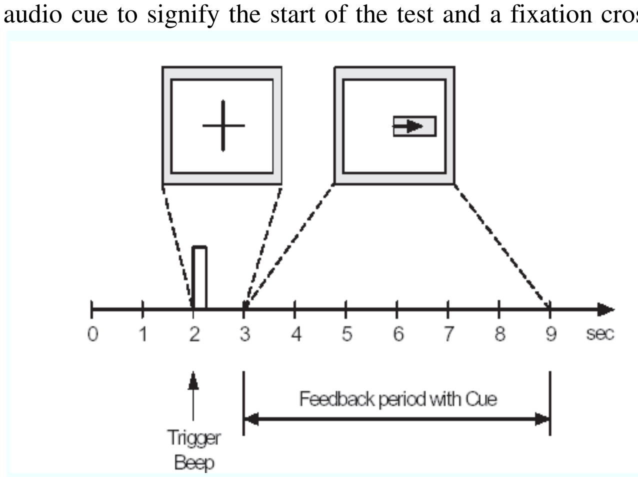

Figure 1. At 2 seconds into the trial a fixation cross appears and an audio cue is sounded. At 3 seconds into the trial a randomly selected left or right arrow is displayed and at this point the subject imagines moving the hand on the side of their body that corresponds with the direction of the arrow. At 9 seconds the trial ends and the next trial begins [4].

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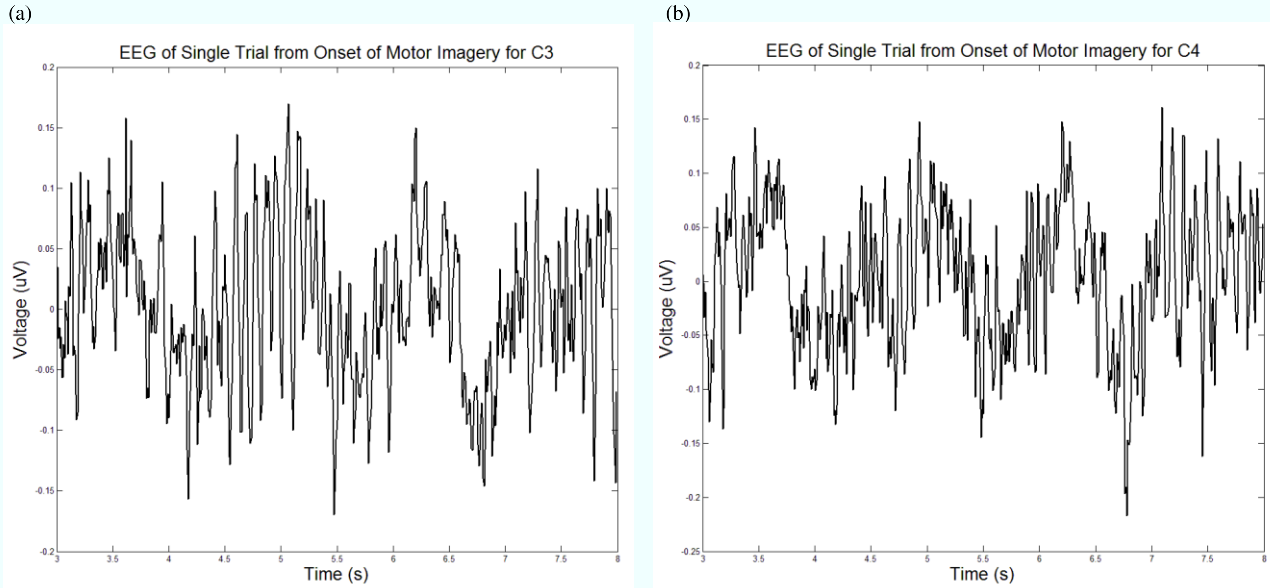

Figure 2. (a) The raw EEG data from a single trial from (a) channel C3 and (b) channel C4, at the onset of motor imagery.

displayed for one second. At three seconds into the trial a left or right arrow was displayed for six seconds to indicate which hand to imagine moving. A feedback bar was also displayed to the user during this time to help indicate the success of the imagined movements. The trial lasted nine seconds in total. 280 trials were recorded on the same day with several minutes rest every 70 trials. The trials were then randomly sorted into training and test groups, with 70 trials of imagining left and 70 trials of imagining right forming the training data group, and the remaining 140 trials forming the test data group. The EEG was sampled at 128 Hz and band-pass filtered to between 0.5 and 30 Hz.

B. *Feature Extraction*

EMD is a process for separating a waveform into a group of harmonics and residual noise. It is achieved by applying the following steps to the data, $x(t)$:

i.) Identify the maxima and minima of the signal.

ii.) Interpolate between the maxima and minima to create upper and lower envelopes.

iii.) Calculate the mean between the two envelopes, $m(t)$.

iv.) Subtract the mean from the signal to get an IMF candidate, $x_{n+1}(t) = x_n(t) - m(t)$.

v.) Check if $x_{n+1}(t)$ is an IMF by calculating if it is symmetrical with respect to zero

a.) If $x_{n+1}(t)$ is an IMF then store the IMF and return to step i.) with the signal $x(t) = x_n(t) - x_{n+1}(t)$.

b.) Or if $x_{n+1}(t)$ is not an IMF then discard and

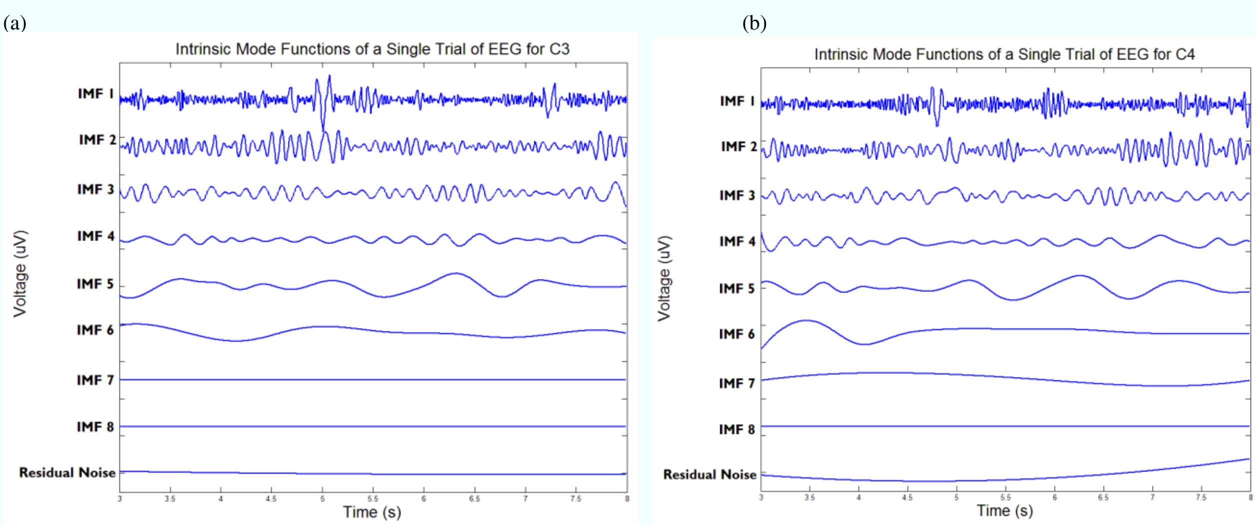

Figure 3. (a) The IMFs and residual noise produced from applying EMD to the data shown in Fig 2a. Summing these plots would reform the plot in Fig 2a. (b) The IMFs and residual noise produced from applying EMD to the data shown in Fig 2b. Residual noise from both channels will be discarded and the next step is to cluster the IMFs of both channels together in preparation for isolating the IMFs that span the μ rhythm frequency band.

return to step i.) with the signal $x(t) = x_n(t) - x_{n+1}(t)$.

vi.) When there are less than two extrema left in the signal the remaining data is classified as the residual.

The above process was applied to the data from electrodes C3 and C4 (shown in Fig. 2) of each individual trial at the onset of motor imagery until one second before the end of the trial (3-8 s). The residual noise was immediately discarded and the IMFs (shown in Fig. 3) of both electrodes grouped together so that the data from more than one channel was included. Fast-Fourier Transforms (FFTs) were calculated for each IMF. The peak frequency of each IMF and its corresponding amplitude were identified. These peak frequencies were grouped into clusters using Hierarchical Clustering Analysis (HCA), ensuring that IMFs spanning similar frequency bands were grouped together (shown in Fig. 4). HCA calculates the Euclidean distance between every possible pair of data points and constructs a binary hierarchical cluster tree with the pair of elements with the smallest distance between them forming the next link [5]. The tree is then partitioned into separate clusters when there is a sudden increase in the distance between links. This algorithm ensures the grouping by peak frequency values is done objectively.

The cluster that spanned 9-11 Hz was identified as the μ rhythm cluster (shown in Fig. 4). Should excessive artifacts or noise distort the signal to the extent that no clusters spanning 9-11 Hz were detected, the frequency band was expanded by 1 Hz in both directions until a cluster fell within it. This was so that trials which had had their μ rhythm obscured by noise still could contribute some data that could be used to classify them, rather than be discarded completely. The electrode source of each IMF in the μ rhythm cluster was identified and the amplitudes of the peak frequencies of IMFs from the same electrode summed together, producing a single value for each electrode (shown in Fig. 4). This value represents the power in the μ band for an individual electrode, giving us amplitude, frequency and spatial data. After that a simple comparison of the values' magnitudes is enough to determine which hand the subject was imagining moving, with greater power in C3 meaning the subject was imagining moving their left hand and greater power in C4 meaning the subject was imagining moving their right hand. This difference in magnitudes corresponds to the theory of μ rhythm suppression on the contralateral side of the motor cortex during a motor imagery task.

III. RESULTS AND DISCUSSION

The classifier described above resulted in 88.57% specificity and 88.57% sensitivity, subsequently identifying 88.57% of the 140 test trials correctly. Each trial required 5 seconds worth of data and 0.30 seconds of processing time, giving an information throughput of 11.32 bits/minute. Fig. 5 shows the calculated difference between the power in the electrodes. It shows a clear left-right distribution, demonstrating visually in this case the redundancy of a trained classifier such as Linear Discriminant Analysis (LDA) or Support Vector Machines (SVM) [6]. For the sake of completeness, the processed data from the training and test sets was processed through an LDA classifier and it returned the same accuracy as the simplified threshold classifier, thus showing that a non-complex classifier is sufficient due to efficient feature extraction of the data. Although the method is only applied to one test subject it does provide a proof-of-concept that EMD can be used on EEG data this way. The minimum requirement of 5 seconds worth of data is a minor disadvantage compared to alternative methods that can start giving online feedback as soon as the trial starts.

Table 1 lists a selection of methods applied to this data set sorted by accuracy, with the method described in this paper coming third, demonstrating comparable performance to existing methods. Requiring no training trials at all in order to construct a classifier is a distinct advantage in ease of use and reducing processing time. The frequency boundaries of the μ rhythm do need to be defined before executing the process and they may vary slightly between subjects. This could be avoided by taking an average of all the trials' EEG data and calculating an FFT. There would be

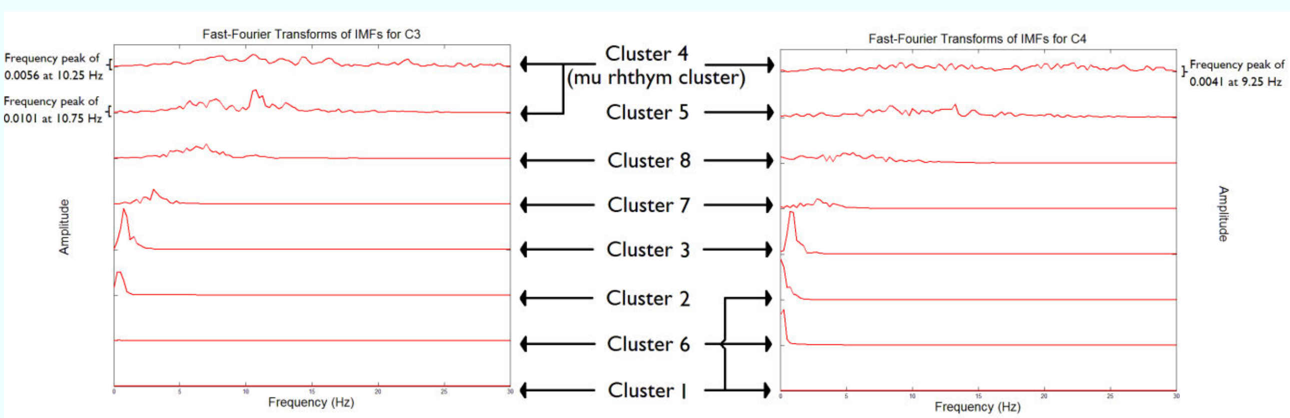

Figure 4. The FFTs calculated from the IMFs in Fig 3a and 3b. The peak frequencies of the IMFs have been clustered to determine which FFTs, and by extension which IMFs, are most similar to each other. Then the cluster that consists of peak frequencies within the μ rhythm is identified, in this case Cluster 4. The amplitudes of the peak frequencies in the IMFs from each electrode are summed and compared, e.g. 0.0157 (0.0056 + 0.0101) in channel C3 vs 0.0041 in channel C4. The μ rhythm is less and has therefore been suppressed more in channel C4, therefore the hand contralateral to it (left) was imagined being moved in this trial.

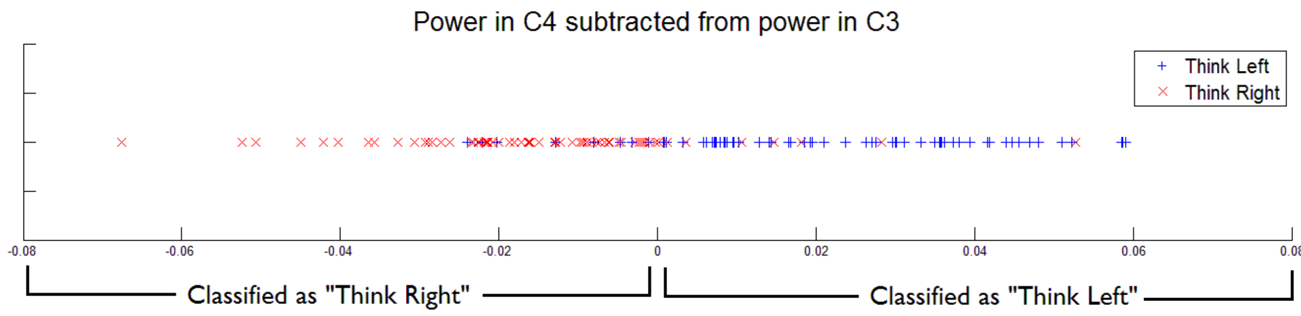

Figure 5. Difference in calculated power between channels C3 and C4. After the power in the μ rhythm for each electrode has been calculated the two values are compared, with the channel with less power being the one that is contralateral to the imagined movement. Were you to subtract the value in C4 from the value in C3, any trials where the μ rhythm power was less in C3 would give a negative result and trials where the μ rhythm power was less in C4 would give a positive result. Therefore any subtraction that gave a negative result would be identified as "Think Right" by the classifier and any subtraction that gave a positive result would be identified as "Think Left". The correct direction the user was thinking of is denoted by the different colored markers. The spread of the markers has a strong left-right divide over the threshold point (zero).

a distinct peak over the frequency band the μ rhythm was occurring at. This would provide a way to objectively select the frequency band and cluster of interest. However it would reintroduce the need for training data. As EMD is data-driven and adaptive it has further possible applications to BCI outside of motor imagery.

IV. CONCLUSION

EMD has proven to be a robust method in creating filters that mold themselves to the data it is applied to, producing features so distinct that a linear classifier with no supervised training can be applied to them. HCA on the other hand may be superfluous to the process. An alternative method for selecting the relevant FFTs (and the IMFs that they were calculated from) could be to simply keep those that had peak frequencies within the μ rhythm frequency band and discard the rest. Possible future work on this method would include applying it to data that was recorded with significantly more electrodes in order to evaluate the impact of multi-channel EMD on the classifier's accuracy, objectively identifying the boundaries of an individual subject's μ rhythm through the use of averaged training data and investigating the possible usefulness of the 20 Hz rhythm that has been observed during some motor imagery activities [9].

TABLE 1. COMPARISON OF MINIMUM ERROR RATES SUBMITTED BY DIFFERENT GROUPS FOR THE SAME DATA*

Authors	Method	Error Rate (%)
Xu *et al*	Wavelet Transform	7.90
Schafer *et al*	Wavelet Transform	10.57
Davies *et al*	EMD	11.53
Xiaorong *et al*	ERD	13.57
Xiaorong *et al*	ERD	15.00
Narayana *et al*	AR Modeling	15.71
Saffari *et al*	AAR Modeling	17.14
Sadashivaiah *et al*	AR Modeling	17.14
Zander *et al*	AAR Modeling	17.14
Rissacher *et al*	Spectral Entropy	23.57
Rio Vera *et al*	PCA	32.14
Mbwana *et al*	PPDA	49.29

*Results, excluding *Xu et al* [7] and *Davies et al*, aggregated by *Jia et al* [8]. Error rate is calculated by applying the group's selected processing method to a training set and test set. A moving window of one sample's length is swept across the processed data. For each window an LDA classifier is trained using the training data within the window and applied to the test data that falls within the moving window. The window that produces the lowest error rate is selected as the optimum sample point.

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