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Classification of EEG Signal for Movement Intentions-based Brain Computer Interfaces

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Abstract *:* Brain Computer Interface (BCI) is a new feature of human-machine interaction for a direct communication channel from the brain. It involves the extraction of information from brain activity and translates it into system commands using feature extraction and classification algorithms. The study uses signals previously recorded in the BCI lab. Feature selection and classification were based on the Neural Network (NN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). The results of classification show that LDA classifier recorded the highest accuracy in 3 and 4-class of movement compared with SVM and NN classifiers. LDA classified the 4-class of movements at central channel and single channel with the average accuracy of 43.75% and 42%. Further, LDA performed better result in 3-class of movement, with an average accuracy 62%. The highest accuracy for bandpower performed by LDA classifier with average accuracy 41.75 % at beta band.

Key words: EEG, Linear Discriminant Analysis (LDA), Neural Network (NN), Support Vector Machine (SVM) and

INTRODUCTION

BCI systems establish a direct communication channel from brain to computer [1, 2]. Normally, people use speech and movement as communication channel to covey message but BCI uses signals of brain activity, recorded from the scalp and transformed into a control signal. Since BCIs do not depend on muscles, they able to communicate with the brain despite severe physical disabilities such as spinal cord injury, brainstem stroke and amyotrophic lateral sclerosis (ALS). BCI research has seen rapid growth all over the world in recent years. Current work focuses on people with severe movement disorders. BCI research really got started in the 1990’s, when advanced computing and enhanced EEG devices presented new potential for BCI. There are more than 20 BCI research groups to investigate and explore novel aspects of BCI systems.

For the purposes of this research, movement intentions relating to motor imagery correspond to μ-rhythms. Activities related to motor imagery in the μ-rhythm are event-related (de)synchronizations (ERD/ERS). In the μ-rhythm, ERD is attenuation which accompanies movement intention. During the thought process, the amplitude of ERS will increase [3] and ERD will occur. This is known as motor imagery. This mechanism makes the cognitive task appropriate for people with motor disabilities. Therefore, the central cognitive task involved is, simply, imagination – for instance, the imagined movement of each hand. In other related work, we find motor imagery involving other somatosensory output [4, 5, 6].

The motor pathways of the central nervous system are also involved in BCIs. By using fMRI, PET and implanted electrodes, specific areas of the brain involved in motor movements are predicted [7, 8, 9]. The data thus obtained is analyzed by principal component analysis, independent component analysis (ICA) or LDA to show the extent to which the strength of the signal detected by the brain correlates to motor activity [10, 11, 12]. It shows that individual variations surrounded by subjects, the certain area in brain are related to certain functions. The first person to make a scientific attempt to categorize areas of brain by their respective functions was Korbinian Broadman. He used tissue samples to segregate the brain into its distinct components. Present studies use far more advanced methods to detect brain signals, like fMRI,PET and EEG [12, 13].

At present study, the research in movement intention is becoming one of the attractive areas to explore and analyse the human movement intention. Indeed, the BCI group from University of Essex especially F. Sepulveda and I. Navarro explored EEG recording by using linear and quadratic classifiers, multilayer perceptrons (trained by back-propagation or gradient-based methods) and radial basis function networks to different types of wrist movement including left and right flexion, extension, pronation, and supination [14, 15, 16]. In addition , Jonathan R. Wolpaw and Dennis J. McFarland from the Laboratory of Nervous System Disorders,New York have claimed that better EEG control in BCI systems able to measure EEG which recoding the EEG on the scalp to control accurate movement of a cursor in two dimensions [17].

This paper aims to analyse the signal of movement intention and identify feature selection and translation algorithms. Thus, the classification has been carried out based on the Neural Network (NN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). Apart from that, the aims of this paper is to study the capabilities of the EEG signals to detect and aid in the prediction of movement intentions.

METHOD

Measuring EEG

EEG signals are recorded with a radius 5 mm which placed on the scalp by small silver/silver chloride electrodes (see figure 1). In order to improve conductivity between scalp and electrodes, conductive gel is required. Normally, an electrode cap is used to attach the electrodes to the scalp. It is important to record the signal with respect to reference electrodes.

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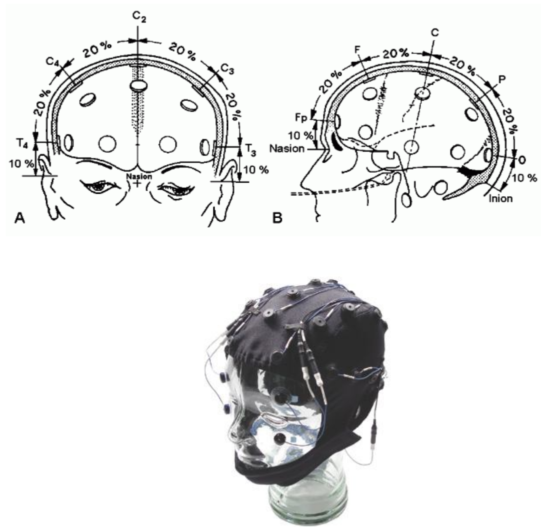

Fig 1: Electrode placement for EEG [18].

Available Data

This research will use recorded data 4-class of movement available in the BCI laboratory at the University of Essex [45]. This available data will continue to the next step of BCI system which are feature extraction and feature classification. Based on directions in the paper by A.Vuckovic and F.Sepulveda [17], the 4-class of movement, it has recorded from ten healthy volunteers,8 men and 2 women. They performed four types of real and kinaesthetic imaginary right wrist movements which are extension (E)/flexion (F), and pronation (palm down P)/supination (palm up S). For every trial, there were 4 different movements associated with 15 repetitions. Recording was carried out using a 64-channel BiosemiTM ActiveTwo system. Further from the 4-class of movement, this study will identify the band power of that movement in order to find values of energy.

In addition, another dataset consisting of 3-class of movement which involve right wrist, left wrist and imagine foot movement are used to analyse and compare with 4 classes of data for better result in this thesis. The data set of 3-class of movement was 5 channels, 360 trials and 1537 samples, [5x360x1537].

Feature Extraction

Feature extraction is implemented because it allows for easier analysis and improved classification performance. For the purposes of this project, an epoch started at t=0 s and finished at t=3 s. This epoch acts as the range within which to analyse signals, making for easier as well as more accurate measurements of the specific signal based on the classifiers. In feature extraction of this project, the channels or EEGs were referenced to the right ear which is 65. In order to minimise noise, the Butterworth filter was applied. Then, a high pass cut off frequency from 3 Hz to 100 Hz and low pass cut off frequency at 50 Hz. The EEG data was then filtered to obtain five datasets consisting of delta (1- 4Hz), theta (4 -7 Hz), alpha (8 - 13Hz), beta (14 - 30Hz), and gamma (26 - 70Hz) bands. After extracting all these bands, a random set was generated and divided into two sets parts - the training set and the testing set. At this point, training and testing sets play the important role of helping to setup the dimension of training and testing, which enables us to continue with all the classifiers.

Feature Classification

The translation algorithm should enable the practical application of the above-mentioned concepts. It is the translation algorithm that indicates the function with which to represent the brain state in BCI system. The practical implementation of the concepts mentioned before should be continued by the translation algorithm which is the classification of the acquired features. In fact, the translation algorithm will indicate the function to represent the brain state in BCI system. In this project, classification will have effect on the device control and it can be achieved in many ways as below:

- Linear Discriminant Analysis
- Neural network
- Support Vector Machines

A. Linear Discriminant Analysis

In order to identify the differences between multivariate classes and determine the signals between the classes, this project applies LDA in order to separate the signals in different classes. Additionally, variance and mean values of EEG amplitude are also classified by LDA [29]. LDA would provide the ability to adjust alpha and beta frequency bands to the precise relevant band of the individual subject [30]. The discriminant function:

$$L = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + c = \sum_{i=1}^{n} w_i x_i + c \qquad (1)$$

where x as the input vector
w as the discriminant coefficients
c is a constant.

The distance of this class will be allocated by data point xi and can be determined by the measured vector w. LDA is optimal if the distance between the classes is maximal [57]. The criterion is to be maximized:

$$J(w) = \left|\tilde{\mu}_1 - \tilde{\mu}_2\right| = \left|w^T(\mu_1 - \mu_2)\right| \qquad (2)$$

μ is the average of a class,
w represents the weight vector.

B. Neural Network- Multilayer Perceptron Network

It can be seen that the concept of the NN has a near equivalent in the neuron of the human brain. It is because of the structure of neuron networks that incoming information can be processed and output becomes possible subsequent to this processing as in Figure 2. A central assumption of this study is that Neural Networks can be applied to classify brain signals and waveforms for recognition in the Brain Computer Interface system. In the context of EEG, neural networks have been widely used to analyse EEG signals [21].

The network can be trained by feeding the training-input to the NN with the desired output. Since NN is trained properly, the new (unknown) input from the same system will result in proper classification. In other words, the working and output of the neuron network depends on the incoming input.

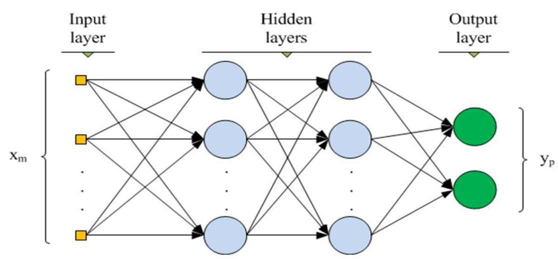

Fig 2: Architecture of Neural Network [19]

In practical, the network was trained by using back propagation of error algorithm. Therefore, the input is fed forward and after which the error is back propagated through the network to update all the weight in the processing elements. This research used the available Neural Network toolbox in Matlab. This network will start at the output layer which the output layer will be compared with the desired output. After training set and testing set were formed, Neural Network ready to train. There were 768 trials in accordance with the last 3 s epochs (last 3s).

C. Support Vector Machine

A learning algorithm that is often used in BCI systems is the Support Vector Machine (SVM). In order to understand SVM clearly, it is essential to consider that all the training examples can be separated by a hyperplane (the case in which the training data is linearly separable) [23, 24]. For SVM optimization, the coordinates of x and y determined w (weight vector) and b (offset) by:

$$\min_{w\in R^d} \frac{2}{w^T w} \quad \text{and} \quad y_i(w^T x_i)+b \ge 1 \qquad (3)$$

A dual problem needs to be constructed using Lagrange multipliers that should be maximized. The equation 4 has the solution. Each non zero α corresponds with ax that is a support vector.

$$w=\sum \alpha_i y_i x_i \ \text{and}\ b = y_k - w^T x_k \ \text{for any}\ x_k \ \text{such that}\ \alpha_k \neq 0 \quad (4)$$

One of the advantages of using SVM is that it is based on a strong theoretical background. This allows us to generalise from results and adds to the efficiency of computation [8]. In practice, SVM training depends on the data points (support vectors) adjacent to the margin hyperplanes [25, 26].

Number of Electrode

This research used measurements from 64 electrodes. Electrode labels are composed of a combination of letters and a number. The letters refer to anatomical structures (Anterior, Frontal, Parietal, Occipital, Temporal lobes and Central sulcus) while the numbers represent sagittal (anterior–posterior) lines. As can be seen in Figure 9, below, the single channel measured C3 and the central channel measured C5, C3, C1, Cz, C2, C4 and C8. The position of these electrodes is illustrated in the Figure 3.

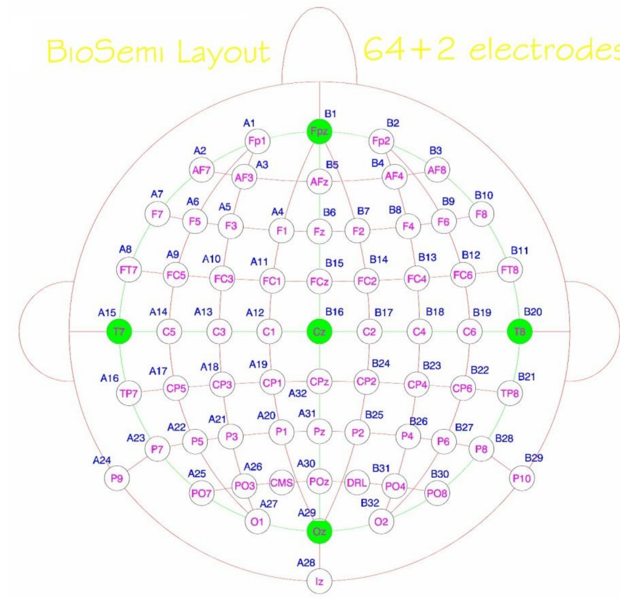

Fig 3: Locations of electrodes and labels of corresponding channel [20].

RESULTS

Generally, there were two sets of data have been investigated; one set with 4 classes of movement and 3 classes of movement. For 4 class of movement, it indicates 67 channels, 60 trials and 1280 samples and the 3 classes consists of 5 channels, 360 trials and 1537 samples. Besides that, the data set from 4-class of movement measured the bandpower.

A. 4 Classes of movement

There were five tests for Neural Network classifier at channel C3. Classification results using Neural Network classifier for single channel are shown in Table 1. Result shows the highest percentage average is obtained by movement 4. An interesting finding is the 44% average of accuracy for movement 4. The reason is thought to be related to the cognitive task involved – i.e. – the rotation of the forearm – and a subsequent increase of motor units. Another factor which contributes to this situation is the characteristic of EEG signal is very noisy. In addition, there were statistically significant differences between movement 4 and the other 3 movements. Movements 1, 2 and 3 obtained 0% during five tests. This thought to be due to the fact that the NN does not have enough degrees of freedoms that facilitated by the processing elements. Therefore, the high error in classification will occur. In [21] the authors reported that having too much processing elements may occur in overfitting to the training data. The stopping criterion was a MSE = 0.0049. In this neural network, a training set consisted of 40 trials and testing set consisted of 20 trials.

Table 2 illustrates the accuracy of classification by using SVM and LDA classifiers. These two classifiers show that LDA classifier performed better than SVM classifier at channel C3. The different average value of LDA and SVM is 6.75%. In fact, however, as further results will show, the SVM classifier performed better than the LDA classifier. It is known that the quality of signal recording affects the performance accuracy of the classifier. The SVM classifier normally measures only 2 classes of movement. For this project however, there were 4 class of movement. As expected, the quality of the recording and subsequently, the accuracy of the classification, were slightly impaired due to the increase in the number of classes.

Table 1: Result of accuracy of testing in Neural Network classifier for one channel

Neural Network Classifier	Test 1 (%)	Test 2 (%)	Test 3 (%)	Test 4 (%)	Test 5 (%)	Average (%)
Movement 1	10	00	15	80	00	23
Movement 2	80	10	00	00	05	17
Movement 3	00	05	70	00	05	16
Movement 4	10	85	15	20	90	44

Table 2: Result of accuracy in Support Vector Machine and Linear Discriminant Analysis for single channel

Test	Support Vector Machine	Linear Discriminant Analysis
Test 1 (%)	33.75	45.00
Test 2 (%)	35.00	43.75
Test 3 (%)	32.75	40.00
Test 4 (%)	36.25	41.25
Test 5 (%)	36.50	40.00
Average (%)	35.25	42.00

B. 3- Class of movement

The three classes of movement consisted of movement of the right wrist, the left wrist, and imagining movement in the feet. Table 3 shows the accuracy result for the LDA classifier. The plotting time accuracy is illustrated in the graph (Figure 4, below).

Table 3: Result of accuracy in Linear Discriminant Analysis

Test	Linear Discriminant Analysis (LDA)
Test 1 (%)	65.00
Test 2 (%)	60.00
Test 3 (%)	60.00
Test 4 (%)	55.00
Test 5 (%)	70.00
Average (%)	62.00

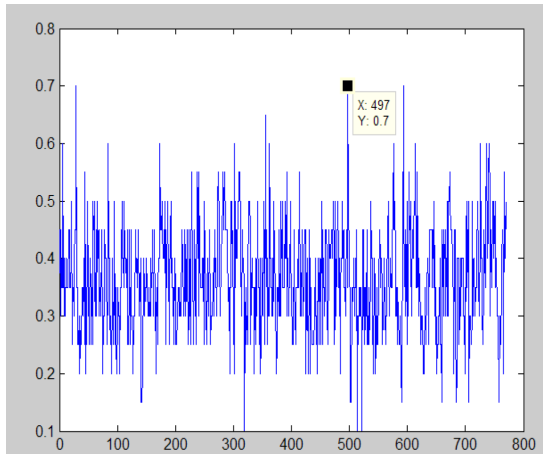

Fig 4: The accuracy value of one of the test (test 5) in LDA.

The result as in table 3 shows that LDA achieved better performance in 3 classes of movement than 4. The reason relates to the fact that LDA only considers a single linear transformation in a global coordinate system and the transformed face classes are still multi-modally distributed. The results of accuracy for the SVM classifier are presented in Table 4 and result of accuracy in Figure 5.

Table 4: Result of accuracy for 3 classes in SVM

Test	Support Vector Machine (SVM)
Test 1 (%)	45.00
Test 2 (%)	55.00
Test 3 (%)	50.00
Test 4 (%)	65.00
Test 5 (%)	45.00
Average (%)	52.00

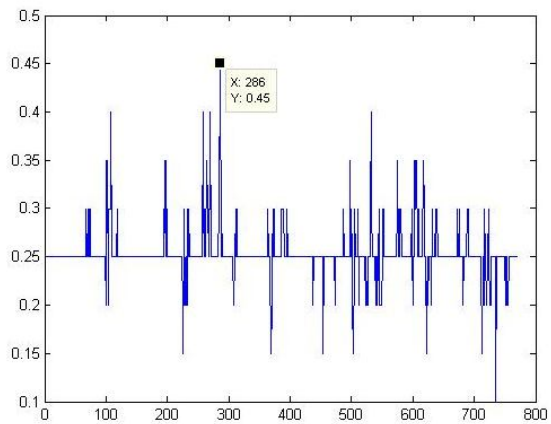

Fig 5: The accuracy value of one of the test (test 1) in SVM.

Tables 3 and 4 clearly illustrate that the results for the set with 3 classes of movement result were more accurate for both classifiers as compared with the set for 4 classes of movement. The average accuracy of the LDA recorder from 5 tests was 62%, while for the SVM classifier, it was 52%. These two results prove that the LDA classifier performed more accurate classification than SVM classifier on this research. These results contradict existing studies and are quite possibly the stem from a paucity of recorded data. Most studies involve 5 to 11 subjects for recording. Moreover, the implementation on the Matlab code was based, in this study, on the built-in function of the programme, without involving complex mathematical theory. In fact, SVM has been successfully implemented for nonlinear classification problems [27]. One reason for the classification accuracy of SVM is that the classification algorithm attempts to find a decision boundary or separating hyper plane in the feature space.

In fact, SVM has been successfully implemented for nonlinear classification problems [28]. One reason for the classification accuracy of SVM is that the classification algorithm attempts to find a decision boundary or separating hyper plane in the feature space. These two figures,10 and 11 show better performance of LDA and SVM classifier compared with the previous results in 4-class of movements. In this case, number of samples for the set of 3 classes of movement had been reduced from 768 to 23 samples. This shows that one factor behind differences in classification accuracy could be the number of samples.

C. Bandpower

Bandpower consists of alpha, delta, theta, beta and gamma waves. These five bands have been identified and used as the input signal for both LDA and SVM classifiers. The previous experiment, the input for all classifiers are is a function of time after extracting according to entire bands. For the purposes of the present study, the energy value of bandpower from each band has been used. The data set of bandpower consisted of measurements taken from 21 electrodes over 60 trials and 23 times point of 1280 (from 4-class of movement). The energy of each band was calculated from the specgram of each movement. Based on the specgram parameter, the data was 129. Based on this dimension, it has been tested to each classifier in order to investigate the highest accuracy to carry significant class related information. Tables 9 and 10 illustrate the accuracy of the LDA and SVM classifiers.

Table 9 shows that after five tests, the beta band recorded the highest accuracy, followed by gamma, alpha, delta and theta. The beta band corresponds to frequencies from 14 Hz until 26 Hz and is most relevant to the movements studied in this research. Table 10 shows the result of accuracy for the all bands in the SVM classifier. Values range between 25% to 25.75%.

Table 9 : Result of accuracy for all bands in LDA classifier.

Band Power	Test 1	Test 2	Test 3	Test 4	Test 5	Average
Alpha	41.25	36.25	40.00	36.25	41.25	39
Delta	40.00	41.25	36.25	42.50	35.00	39
Theta	33.75	37.50	37.50	37.50	35.00	36.25
Beta	40.00	45.00	41.25	38.75	43.75	41.75
Gamma	41.25	46.25	41.25	35.00	38.75	40.5

Table 10 : Result of accuracy for all bands in SVM classifier.

Band Power	Test 1	Test 2	Test 3	Test 4	Test 5	Average
Alpha	25	25	25	25	25	25
Delta	25	25	25	25	25	25
Theta	25	25	25	25	25	25
Beta	25	26.25	26.25	26.25	25	25.75
Gamma	26.25	26.25	25	26.25	25	25.75

CONCLUSION

This research tackled three types of classifiers - NN, SVM and LDA in order to analyse EEG signals related to wrist movement. These movements were identified through two types of classes; 4-class movement, 3-class movement and

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the bandpower. It was found that the LDA classifier offered the highest accuracy in single channel and central channels for 4-class of movement. Further, LDA classifier also showed the highest accuracy for 3-class of movement. In bandpower, beta was found the highest accuracy band for LDA classifier with 41.75%. For all classifiers, channel C1 obtained the highest accuracy in 4-class of movement. With this result, LDA classifier was selected as the most appropriate classification of signal for movement intentions in this research. Significant improvements could be made in relation to the accuracy of these results. A higher number of samples and classes would have yielded more data and therefore improved the accuracy of the statistical analysis and results. The further development of analytic techniques would enable us to study a wider variety of movements.

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