Investigation of the Two Most Discriminative Directions of the Wrist Movement Imagery Tasks

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Abstract

The purpose of Magnetoencephalography (MEG) based brain computer interface applications are to develop machine learning algorithms from small magnetic fields generated by neuronal activity and to make theoretical predictions from these algorithms. In this study, brain-computer interface competition 2008 data set 3 containing modulated MEG signals obtained by performing the imagination of right, left, forward and backward movements of the subjects' wrists were utilized. The aim of this study is to decide which two classes give better classification accuracy by using different classifiers. The signals recorded from this 4-class dataset were first reduced to 2 classes as forward-backward, right-forward, right-backward, left-forward, left-backward and right-left and then different feature extraction methods were applied to these combinations. The classification accuracy of the right-left direction gives best results with the random forest classification using the kurtosis of wavelet transform coefficients of the signals taken from channel 5 and 7 of the 10-channel data set. These two classes were investigated as the most discriminated two-class among the 4-class data set.

1. Introduction

The Brain-Computer Interface (BCI) which consists of signal acquisition and signal processing, uses control channels and other electronic equipment to communicate between the human brain and the computer. The processed signals can be Electroencephalogram (EEG), Electrocorticography (ECoG), Magnetoencephalography (MEG) which are taken from the electrodes placed in different parts of the subject's brain. Among these kind of signals, MEG has not been taken into consideration enough by BCI community.

Electrical field change is known to cause magnetic field change according to the laws of physics. MEG is used to map the brain activity by recording the magnetic fields generated by the electrical currents in the brain. It is difficult to distinguish MEG change, because of its weakness. However, MEG measurements are practical because there is no need for a probe to be connected to the head skin [1], [2].

Many studies have been carried out in the literature for signal analysis with different feature extractions and using various classifiers such as linear classifiers [3], [4] neural networks, non-linear Bayesian, Random Forest (RF) [5], Support Vector Machines (SVM) [6], [7] and k-Nearest Neighbor (KNN) in brain-computer interface applications. Krishna et al. used signal smoothing and curve fitting methods for the classification of MEG signals obtained from four-direction wrist movement. The proposed method was tested by using BCI competition 2008 data set 3 and the classification accuracy (CA) was found as 88.84% [8]. Nasim Montazeri et al. used variance, mean and mode features and found the CA as 62% and 40% for subject 1 and subject 2 respectively by using the same data set. They also investigated the effects of classifiers on CA by comparing SVM, KNN, Bayesian classifiers [9]. Shiyu Yan et al. have shown that the frequency band power and statistical characteristics such as standard deviation and variance are very important features for finding CA of MEG signals. Their method based on Linear Discriminant Analysis (LDA) classifier gave 54.38% accuracy [10]. But Noha and Manal reduced this 4-class dataset into 2 classes as right-forward and left–backward motion. Then, they compared SVM and LDA classifiers by calculating the classification accuracy using same feature vector. In their study, SVM classifier gave approximately 34% accuracy [11].

This study presents an efficient investigation for classifying the two-direction wrist movements in terms of CA among four wrist movement imagery tasks. In order to extract discriminative features, firstly the wavelet transform coefficients (WTC) of the trials were calculated afterwards the max point, variance, kurtosis and skewness statistical values of the WTCs were obtained as features. The CA is calculated using KNN, SVM, LDA and RF classifiers for each combination of classes (forward-backward, right-forward, right-backward, left-forward, left-backward, right-left) separately and it is seen that the CA of right-left wrist movement using RF classification gives the best results.

2. Materials and Methods

2.1. Data Description

In this study, the dataset 3 in BCI Competition 2008 was used. The signals in the dataset were taken from two subjects' wrist movements in four different directions and the goal was to move a joystick towards four different targets using right hand and wrist.

The signals were recorded from 10 MEG channels and filtered by 0.5-100Hz band pass filter and resampled at 400 Hz. The training set consists of 40 trials for each target making 160 trials total for each subject. The test dataset consists of 74 trials for subject 1 and 73 trials for subject 2. This study compares the CA of two-way wrist movements taken from subject 1.

For more information about the dataset, please refer to [12].

2.2. Wavelet Transform

The wavelet transform, which includes both frequency and time components of the signal, is often used as a feature extraction method in MEG signals having different frequency components over time. The continuous wavelet transform (CWT) coefficients used in the study are calculated as given in (1). Here; Y (t), ψ (t), x and y represent the sign, wavelet function, scale and step size respectively [13]. The wavelet model and other parameters used in the study, which provide the highest CA, are empirically determined.

$$WTC(x,y) = x^{-1/2}\int_{-\infty}^{+\infty} Y(t)\psi\left(\frac{t-x}{y}\right)dt \qquad (1)$$

2.3. Feature Extraction

In this study, the feature extraction of the MEG signals is done using the wavelet transform method. We empirically decided that 5^{th} and 7^{th} channels provided more discriminative features. Hence, we used those of channels for feature extraction and classification. The extraction steps of each feature are given in Fig. 1. As it is seen, the feature vectors are obtained by applying maximum point, variance, kurtosis and skewness to the wavelet transform coefficients of the signals from both 5^{th} and 7^{th} channels.

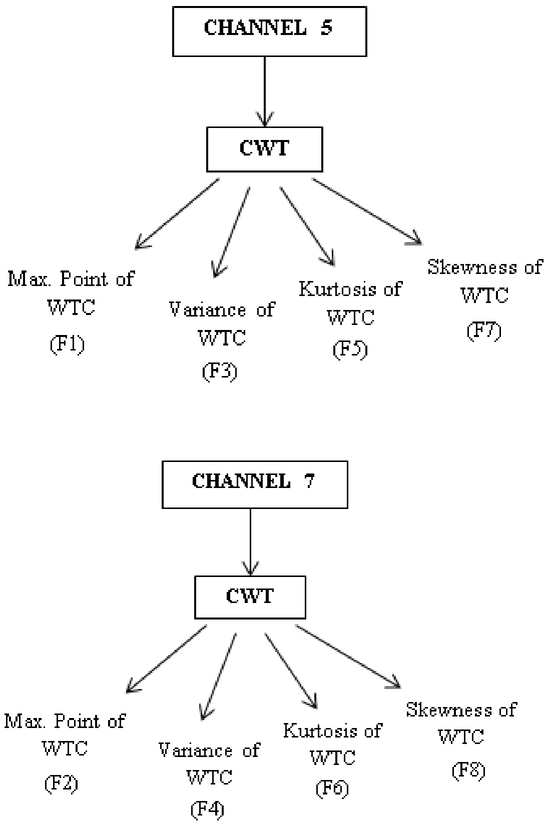

Fig. 1. Feature extraction steps applied to wavelet transform coefficients of signals from channel 5 and channel 7

2.3.1. Variance

Variance is the measure of the propagation of the signals features. In this study, the wavelet transform coefficients of the MEG signal are found and the distance between these coefficients and the mean is determined by the variance. It is calculated as shown in (2).

$$Var\ (WTC) = \frac{1}{n}\sum_{i=1}^{n}(WTC_i - \ -\overline{WTC})^2 \qquad (2)$$

2.3.2. Kurtosis

It's the measure of how much the signal resembles to a Gaussian distribution. The kurtosis density is as in (3). σ is the standard deviation of WTC values.

$$k = \frac{E(WTC-\mu)^4}{\sigma^4} \qquad (3)$$

2.3.3. Skewness

Skewness determines how the distribution of the signal's features differs from the normal distribution. In a normal distribution, the graph is symmetrical to the maximum point. The average and maximum points are equal in the symmetrical parts. In this study, how much the wavelet transform coefficients of the MEG signal from the subjects are different from the normal distribution is discussed. It is calculated as given in (4).

$$S = \frac{\frac{1}{L}\sum_{i=1}^{L}(WTC_i-\overline{WTC})^3}{\left(\sqrt{\frac{1}{L}\sum_{i=1}^{L}(WTC_i-\overline{WTC})^2}\right)^3} \qquad (4)$$

2.4. Classification

In this study, to identify the two most effective classes, LDA, SVM, KNN and RF classification methods are used in each class combination. The success of the features has been examined with 10 fold cross validation. In this cross-validation, training data is divided randomly into 10 equal parts, one of which is used as the validation data and the remaining data is used as the training data. Each piece is considered to be validation data respectively and the parameter giving the highest CA of each segment is obtained. These steps are repeated 100 times to obtain optimum parameters and the parameters are used in the classification of test data.

2.4.1. KNN

Among the machine learning methods, KNN is one of the simplest methods to be applied. It determines the nearest k neighbour of the data to be classified. Then the data is classified according to the classes these neighbors belong. Euclidean distance is used when computing neighbouring distances in the study.

2.4.2. SVM

In SVM, the goal is to find the line which maximizes the distance between classes. This line can be true linear or nonlinear function. The functions and parameters giving high CA are used in the study.

2.4.3. LDA

In this method, the line which maximizes the variance between the classes and minimizes the variance within the classes is tried to be found. It is assumed that the data has a normal distribution.

2.4.4. RF

The RF is a classifier consisting decision trees and nodes. This classifier uses the best of the randomly selected variables at each node when dividing the nodes into branches. According to the internal errors of the decision trees (Out of Bag, OOB), each node is given a specific weight. The decision tree with the lowest fault has the highest weight, while the decision tree with the highest fault has the lowest weight. Voting is done according to these weights. After the votes are collected, the final decision is made [14].

3. Results and Conclusion

The experimental results showed that 5^{th} and 7^{th} channels provide the higher CA values. The classification accuracies of the combinations of 2-direction wrist movements were compared using KNN, SVM, LDA and RF classifiers for F1+F2, F3+F4, F5+F6, F7+F8, F1+F3+F5+F7, F2+F4+F6+F8, F1+F2+F3+F4 and F5+F6+F7+F8 feature combinations shown in the figures.

The performances of the classifiers for the given feature combinations of forward-backward imagery tasks are shown in Fig. 2. In each combination, the percentages of the CA obtained using test data were compared. The KNN classifier gave the highest (62.21%) CA by using F3+F4 features while the F1+F2 features classified by RF gave the lowest.

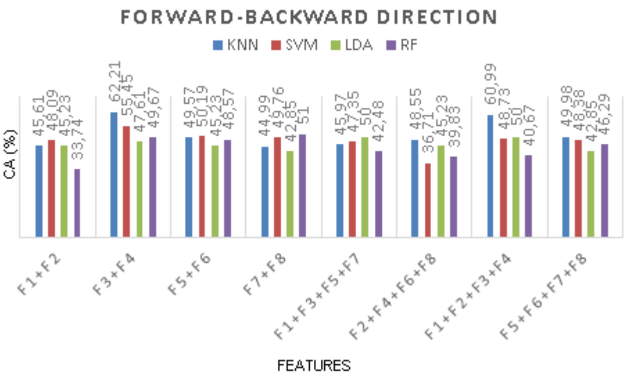

Fig. 2. CA results of forward-backward imagery tasks

The CA results for different feature combinations and classifiers for right-forward imagery tasks are given in Fig. 3. As it is seen the SVM classifier gave the highest CA (65.59%) by using F7+F8 features. The lowest results were obtained using the F5+F6 features with LDA classifier

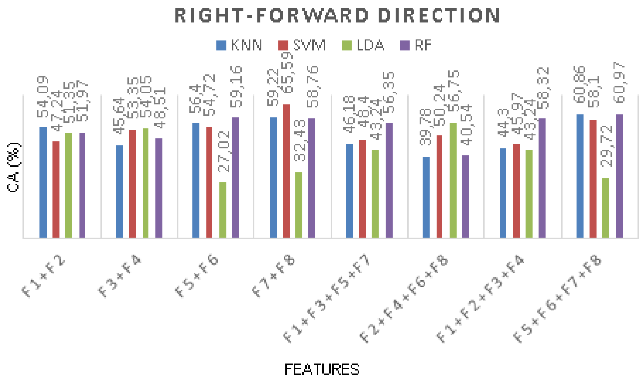

Fig. 3. CA results of right-forward imagery tasks

Fig. 4 shows the percentages of the CA using only the right-backward class of test data. While the LDA classifier gave the highest (62,79%) CA by using F5+F6 features, SVM gave the lowest CA (39,74%) by using F1+F2+F3+F4.

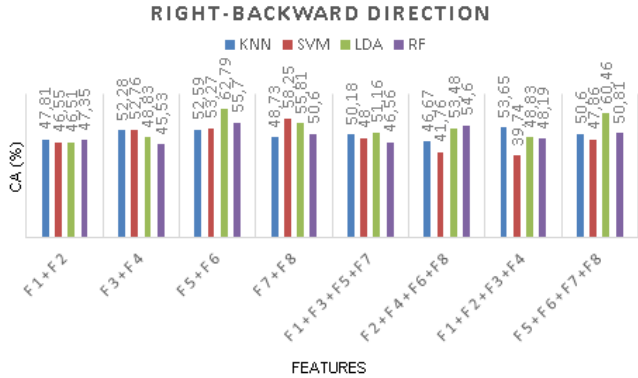

Fig. 4. CA results of right-backward imagery tasks

In Fig. 5, the CA values of left-backward imagery tasks are shown. Seen from the figure the RF classifier gave the highest CA (60,06%) by using F2+F4+F6+F8 features, SVM gave the lowest CA (31,66%) by using F7+F8.

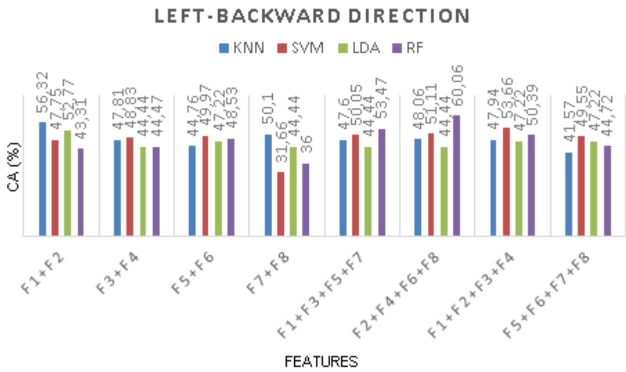

Fig. 5. CA results of left-backward imagery tasks

According to the performances of the classifiers for the given feature combinations, the CA percentages of left-forward imagery tasks are shown in Fig. 6. RF classifier gave the highest CA (61.9%) by using F5+F6 features, the lowest result was obtained as 36.34% by using F1+F2 features for the same classifier.

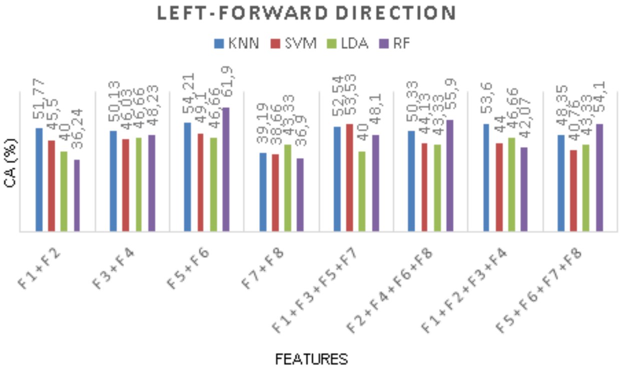

Fig. 6. CA results of left-forward imagery tasks

As shown in Fig. 7, the CA of the right-left movement using the F5+F6 features is 77,32% with RF classification. Whereas the lowest result was found with SVM classifier and F1+F3+F5+F7 features. Generally, all classifiers gave the highest CA with F5+F6 features for right-left imagery tasks.

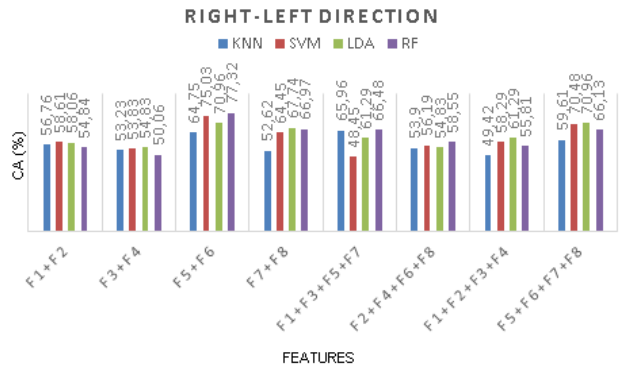

Fig. 7.CA results of right-left imagery tasks

Taking all these factors into consideration, while the right-forward movement is the lowest discriminative of the data set, the CA of the right-left movement of the data set is the most discriminative direction compared with the other 2-direction wrist movement combinations. It can be concluded that by using right-left movement imagery tasks, a more accurate two-class on BCI system might be utilized.

7. References

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