A STATISTICAL FEATURE EXTRACTION IN WAVELET DOMAIN FOR MOVEMENT CLASSIFICATION: A CASE STUDY FOR EYES OPEN, EYES CLOSED, AND OPEN/CLOSED FIST TASKS

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ABSTRACT

Analysis of brain signals constitute an importance, especially for paralyzed people or people suffer from motor disabilities. For this aim, some studies have been evaluated to measure signals from the scalp to provide non-muscle control arguments. Brain-Computer Interface Systems turns these signals into device signals that are controllable at the level of thought. In this paper, we classify diverse tasks according to EEG (electroencephalogram) signals. Then pre-processing, feature extraction and classification steps are hold. For classification, we use FLDA, Linear SVM, Quadratic SVM, PCA, and k-NN methods. The best result is obtained by using k-NN.

Keywords**:** EEG, electroencephalogram, wavelet transform, feature extraction, classification.

INTRODUCTION

The analysis of EEG signals plays a crucial role in brain related works. Many people suffer from motor disabilities need augmentative communication technology. Those are totally paralysed cannot use conventional augmentative technologies, all of which require some measure of muscle control. Over past two decades, some studies have been evaluated the possibility of recording signals from scalp or from within the brain provide non-muscle control arguments [1-8]. Brain computer interface (BCI) systems turn these signals of brain activities into controllable device signals [9,10].

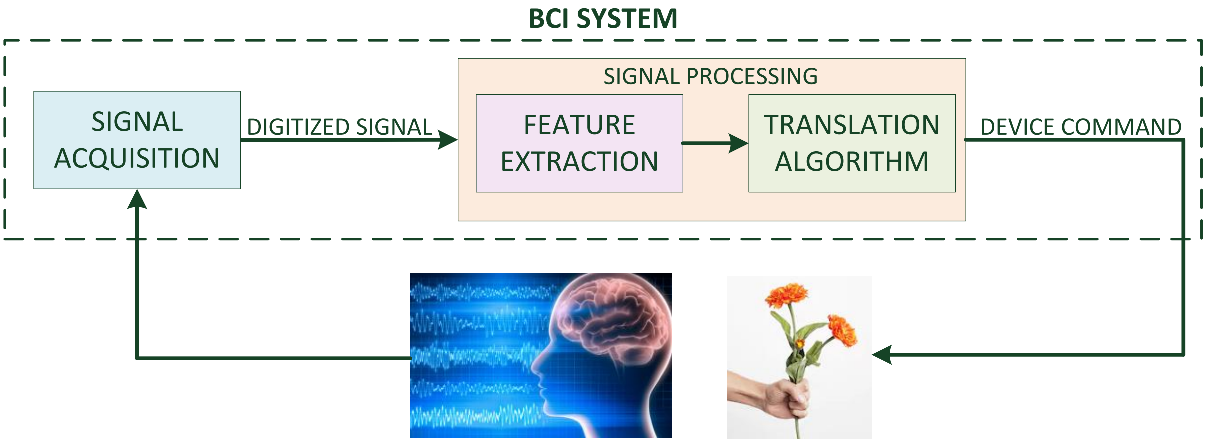

Fig. 1. Basic design and operation of any BCI system. Signals from the brain are acquired by electrodes on the scalp, the cortical surface, or from within the brain and are processed to extract specific signal features that reflect the user's intent. Features are translated into commands that operate a device (e.g., a simple word processing program, a wheelchair, or a neuroprosthesis)[9].

EEG signal is the method that measures brain waves with the electrical signals of the monitoring activities. It can be observed in the literature that, especially the spectral analysis of the EEG signals contains important information about the functioning of the brain dynamics.

Classification of motor movements is a crucial problem in the field of BCI for immediate applications. Such as, significant amount of work has done so far for classification methods for distinguish between various motor movements (i.e. closing and opening eyes, moving right or left hand etc.) by using executed motor movement of EEG signals.

We classify different movement tasks according to EEG signals. These tasks are eyes open, eyes closed, and open or closed right or left fist. All steps we applied is pre-processing, feature extraction, and classification. For classification methods we used Fisher Linear Discriminant Analysis (FLDA), Support Vector Machine (SVM),

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Quadratic Support Vector Machine (QSVM), Principle Component Analysis (PCA), and k-Nearest Neighbourhood (k-NN), and the best result among all is obtained by using k-NN.

WAVELET TRANSFORM

Despite Wavelet Transform (WT) is a new method, it is a fact that to say a considerably growth both in theory and practice of wavelets occurred in the past decade. Wavelets are mathematical tools that divide the signal into different frequency component and examine each component individually. Depending on the frequency, the basis functions of WT are scaled. There are different small waves also known as mother wavelets that may be used for implementation of WT [11]. The mother wavelet function is a window that moves forward in time. Dubachies, Haar, Symlet, Coiflet, Mexican Hat, Morlet wavelets can be given as some of the different type of wavelets and each of them has a different type of properties. When we decide to apply these wavelets, we choose the right wavelet form depending on the requirement of the application.

The main idea behind WT is decomposing the signal different frequency level of coefficients. There are two types of WT defined as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). In our work, we use DWT that is why next we will shortly mention about it. DWT is an implementation of WT using mutually orthogonal set of wavelets defined by carefully chosen scaling and translation parameters. This leads to a very simple and efficient iterative scheme for doing the transformation [12]. The translation equations (Eqns. (1) and (2)) is given by:

$$DWT[n, a^j] = \sum_{m=0}^{N-1} x[m].\psi_j^*[m-n], \quad (1)$$

$$\psi_j[n] = \frac{1}{\sqrt{a^f}}\psi\left(\frac{n}{a^f}\right) \quad (2)$$

where n is delay parameter, N is the length of the signal, ψ is the discretised mother wavelet.

Since in DWT, computation performed on discrete wavelets, it provides a significant yield in terms of computational time. Therefore, DWT is useful when compression of the signal is needed. However, this property comes at a price, especially when the main purpose is to analyse data to discover hidden information [13].

STATISTICAL FEATURE EXTRACTION

After filtering the data, we extracted distinctive features of EEG signals for the usage of training models. We extracted time domain features such as mean, median, variance, standard deviation, kurtosis, skewness of the signals. EEG signals have the non-stationary and the transient characteristics, so only time domain features are not enough for classification. For this aim, we applied Discrete WT method to EEG signals. This method in time frequency domain and it is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis, and is it is well suited to locating transient events.

EEG signals are decomposed into 5 sub-bands: delta, theta, alpha, beta and gamma. They are in different frequency ranges as seen in Table 1.

Table 1. Frequency ranges and the corresponding decomposition levels of sub-bands

Decomposition Level	Sub-band Signal	Frequency band (Hz)
1	D1 (gamma)	30-60
2	D2 (beta)	15-30
3	D3 (alpha)	8-15
4	D4 (theta)	4-8
4	A4 (delta)	0-4

We decomposed EEG signal into 5 sub-bands using DWT, and found coefficients of these sub-bands. Then, we extracted features of coefficients that belong to each sub-band. These features:

- Maximum of the wavelet coefficients of each sub-band (A4,D1-D4).
- Minimum of the wavelet coefficients of each sub-band (A4,D1-D4).
- Mean of the wavelet coefficients of each sub-band (A4,D1-D4).
- Standard deviation of the wavelet coefficients of each sub-band (A4,D1-D4).
- Variance of the wavelet coefficients of each sub-band (A4,D1-D4).
- Median of the wavelet coefficients of each sub-band (A4,D1-D4).
- Skewness of the wavelet coefficients of each sub-band (A4,D1-D4).
- Entropy of the wavelet coefficients of each sub-band (A4,D1-D4).
- Kurtosis of the wavelet coefficients of each sub-band (A4,D1-D4).

Thus, 45 features are obtained from Wavelet Transform.

Addition to these features, energies of D1, D2, D3, D4 and A4 are used for features. Complexity that is each of the Hjorth parameters is found for signals. Variance of first derivative and second derivative of signals are used as features. As a result, we obtained 60 features and the dimension of the feature matrix is 1440x60.

Table 2. Mathematical representations of features

Feature Name	*Mathematical Representation*
Maximum	$M = max_{ij}(D_{ij})$
Minimum	$m = min_{ij}(D_{ij})$
Mean	$\mu = \frac{1}{N}\sum_{j=1}^{N} D_{ij} \quad i = 1,2,\dots,M$
Variance	$var(X) = \sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2}$
Median	$Median = \begin{cases} \left(\frac{n+1}{2}\right)^{th} term, if\ N\ is\ odd \\ \frac{\left(\frac{n}{2}\right)^{th} term + \left(\frac{n}{2}+1\right)^{th} term}{2}, if\ N\ is\ even \end{cases}$
Skewness	$S = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3}{\sigma^3}$
Kurtosis	$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4}{\sigma^4}$
Entropy [14]	$H(X) = \sum_{j=1}^{N} D_{ij}^2 \log(D_{ij}^2) \quad i = 1,2,\dots,M.$
Energy	$E_i = \sum_{j=1}^{N} \lvert D_{ij} \rvert^2 \quad i = 1,2,\dots,M.$
Derivative	$\dot{x}_t = \frac{x_{t+1} - x_{t-1}}{2\Delta t}$ $\ddot{x}_t = \frac{x_{t+1} - 2x_t + x_{t-1}}{(\Delta t)^2}$
Complexity [15]	$v1 = var(\dot{x}_t)$ $v2 = var(\ddot{x}_t),$ $Complexity = \sqrt{\left(\frac{v2}{v1}\right)^2 - \left(\frac{v1}{\sigma^2}\right)^2}$

EXPERIMENTAL STUDY

DATABASE

Publicly available EEG Motor Movement/Imagery data set from physionet.org is used in this paper, which is also used in [9]. This data set consists of over 1500 one-or two-minutes EEG recordings, obtained from 109 volunteers. Each of them has 14 tasks. In this study, we use 10 subjects and 3 tasks that are baseline eyes open, eyes closed and open and closed left or right fist. Every person contains 64 EEG, each sampled 16 samples per second and utilize 48 of recordings as training group and 16 for testing.

TRAINING PHASE

Normalization process to raw data should be applied to extract features more easily and smooth data. For this aim, moving average filter is used. This filter works like Gaussian filter. Parameters of the filter are amount of filtration and the window size of the filter. The filter parameters are set ideally. We extract 60 features by using the definitions given in section 3.

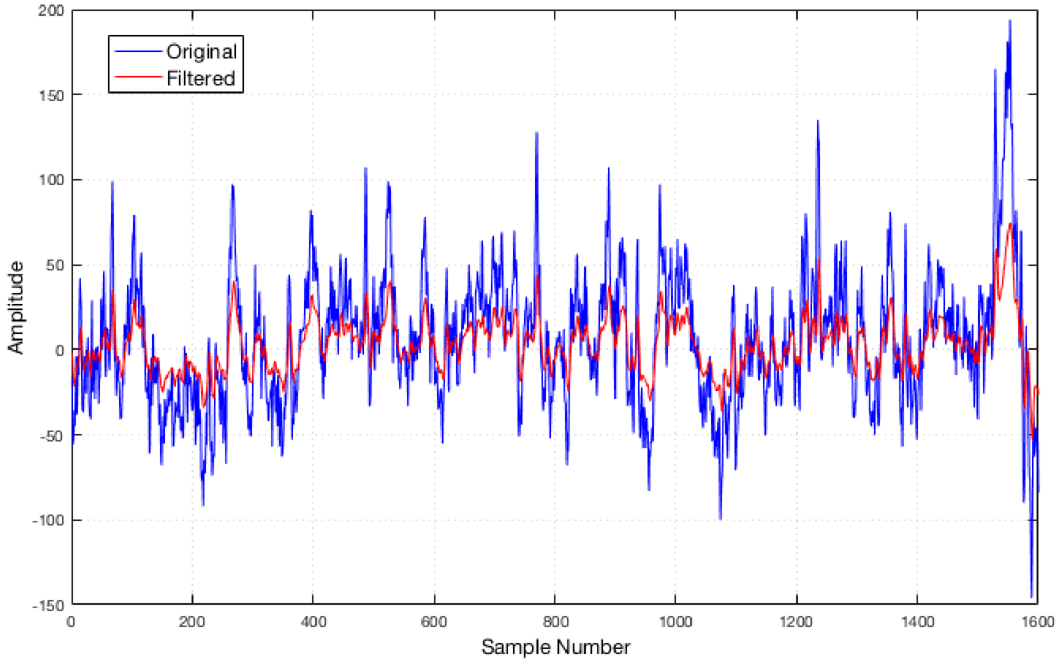

Fig. 2. Original and filtered EEG signals

TEST PHASE

480x60 feature matrix is used for testing. After concatenating training and test matrices, different type of classification methods are applied. Therefore, accuracy rates by utilizing FLDA 66%, Linear SVM 70.6%, Quadratic SVM 86.8%, PCA 87.9%, and k-NN 90.4% are obtained for 60 feature. If approximation component is ignored, 480x51 feature matrix is used in the test phase. Therefore, the accuracy rates change slightly as shown in Table 3. In other words, each feature vector is composed of 51 and 60 features for the without and with approximation component circumstances, respectively.

Table 3. Accuracy rates (%) without and with approximation component

Classification Method	*Feature vector size*	
	51 features	*60 features*
SVM	71.2	70.6
Quadratic SVM	86.9	86.8
k-NN	89.2	90.4
PCA	87.2	87.9
FLDA	65.2	66.0

CONCLUSION

EEG Motor Movement/Imagery data set from physionet.org is used. For three different classes that are eyes open, eyes closed, open or closed right or left fist, 1440x60 feature matrix is built by using mean, median, variance, standard deviation, kurtosis, skewness, derivative and complexity values after a filtering procedure as a pre-processing step. Thus, accuracy rates 66% for FLDA, 70.6% for Linear SVM, 86.8% for Quadratic SVM, 87.9% for PCA is obtained and the best result is obtained 90.4% for k-NN. When the results are reviewed, a slight increase in the k-NN and FLDA classifiers is seen with the increase of the number of features.

Although, there is no significant change for the other three classifiers when the approximation component is added.

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