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A Comparative Study between De-noising Algorithms for Non-Invasive Brain Computer Interface Applications

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Abstract— *Brain Computer Interface provides a communication pathway between the machine and the human. Electroencephalogram (EEG) is a non-invasive technique for acquiring human brain signals. But these non-invasive signals are highly contaminated with several artefacts like Electrooculography (EOG), Electrocardiogram (ECG) etc. Generally EOG artefacts overlap the frequency of EEG signals very firmly. So the de-noising of these signals is a huge challenge to develop Brain Computer Interface based applications. This research shows a comparative study between two major time-frequency domain de-noising methods, Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD).*

Keywords— *Brain Computer Interface (BCI), Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT), Electroencephalogram (EEG), Electrooculography (EoG)*

I. INTRODUCTION

Brain-computer interface (BCI), also known as neural-control interface (NCI) or brain-machine interface (BMI), refers to a human-machine interaction path via brain signals. BCI research started in approx. 1970s. Over the years, the technology has changed dramatically, and over time it is going better. Nowadays, it is a common research topic as it has a strong impact on the development of communication pathways for the people with severe disabilities and other forms of physically challenged people.

Brain Computer Interface nowadays offers the opportunity to study brain signals to detect and diagnose human body disorders. Because every physiological process in our body generates sufficient brain signals. There are different technologies available for recording brain waves. Electroencephalograms (EEG), functional MRI (fMRI) and magneto-encephalogram (MEG) are some of them. This paper uses Electroencephalograph (EEG) signals as it is a part of this research.

Electroencephalogram (EEG) is a non-invasive approach for brain's electrical activity measurement obtained from several electrodes placed on the scalp (Paschalis A. Bizopoulos, 2013). Some highly conductive electrodes are used to capture the brain signals. One of the main issues of the non-invasive approach is the desired EEG signals come with artefacts from eye movements and blinking of the eye. These artefacts are known as Electrooculography (EOG) and considered as signal noises. The process of de-noising these signals is extremely difficult. One of the main reasons for this is that the EOG has a frequency that spreads over EEG signals and also overlaps its frequency.

The purpose of this research is to de-noise the EEG signal from the EOG artefacts. For this de-noising purpose, Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD), two time-frequency domain approaches have been used. And their performance comparison study has been found in two ways: de-noising metrics measurement and prediction accuracy after the classification process.

EEG is an unsteady signal. Discrete Wavelet Transform (DWT) decomposes the signal into details and approximation coefficients. After decomposition process, a soft thresholding technique has been applied to remove noises from the coefficients. After thresholding, the de-noised signal is structured by reconstructing the signal from the details and approximation coefficients.

On the other hand, Empirical mode decomposition (EMD) method (Huang, 1996) is an algorithm for the analysis of multivariate signals (Cohen, 1995). It works by breaking the signal into a number of amplitude and frequency regulated zero mean signals, also known as intrinsic mode functions (IMFs) (Kopsinis, 2008).

Primary efficiency of these algorithms has been calculated by measuring de-noising metrics, i.e. Signal-to-Noise Ratio, Mean Square Error, Mean Absolute Error, Peak Signal-to Ratio Signal, and Cross Correlation.

It is important to find out good features of a dataset to perform a good evaluation. Efficient features have been extracted from the de-noised signals of each de-noising algorithm using some major statistical approach i.e. mean, standard deviation, energy and entropy.

This paper suggested the classification of the model for a supervised machine learning algorithm. For this purpose, Support Vector Machine (SVM) has been used. On their classification accuracy, the comparison study of the performance of two de-noising algorithms has been found.

A four class motor imagery dataset (M. Tangermann, 2012) has been used in this research. Among the four class,

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two classes are used for this paper. These are i) Right hand movement and ii) Left hand movement.

II. PROPOSED MODEL

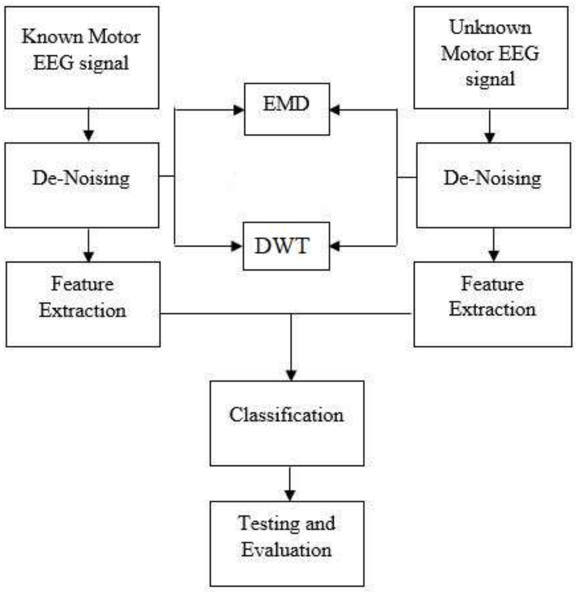

Fig. 1. Proposed Model work flow diagram

In this proposed model, firstly EEG signals are de-noised with two major time frequency domain de-noising algorithms: EMD and DWT. Then de-noising metrics have been calculated for each algorithm and compared. After signals being de-noised, important statistical approach: mean, standard deviation, energy, entropy have been calculated from some selected EEG channels (Michael J. Fu, 2006). On these extracted features, SVM or Support Vector Machine has been applied to classify signals of two motor imagery tasks and train the machine with them. Again, a performance comparison is made among these two de-noising algorithms with the classification accuracy.

A. *Signal De-noising*

Artefacts generally are of two types. One is physiological and another is external (Jog, 2015). EEG signals are often contaminated with several artefacts like EOG, ECG etc. As mentioned before, Discrete Wavelet Transform and Empirical Mode Decomposition, two major time frequency domain method have been used for de-noising purpose.

B. *Discrete Wavelet Transform (DWT)*

The Discrete Wavelet Transform (Krishnaveni, 2006) is the method which breaks down the signal at several frequency links into approximation and details coefficients. It is the discrete form of continuous transformation of the wavelet. The formula is the following:

$$c(x,y)=\int_{-\infty}^{+\infty} s(t)\partial_{x,y}(t)dt$$

Here, $s(t)$ is the main signal and the parameter is x is the dilatation of wavelet and the parameter y defines a translation of the wavelet. $\partial(t)$ is the complex associate of the mother wavelet. The outputs contain some detail coefficients (high-pass filter) and some approximation coefficients (low pass filter).

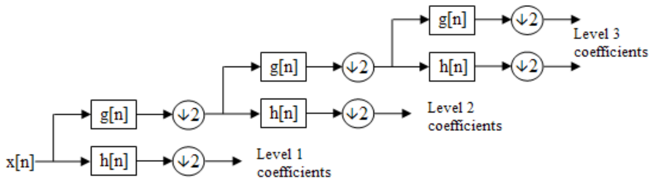

Fig. 2. A three-level wavelet filtering

C. *Empirical Mode Decomposition (EMD)*

EMD comparing Fourier Transforms and wavelet decomposition, which breaks down a signal into several numbers of Intrinsic Mode Functions (IMFs) (Kopsinis, 2008). It uses a shifting process to decompose these IMFs. An IMF is a function which has only one maximal between zero crossings and zeroes as mean value. After decomposing IMFs, it ends up with a residue. Equation of EMD is as follows:

$$Signal(n)=\sum_{m=1}^{M} IMF_m(n)+R_m(n)$$

D. *Feature Extraction*

From all the features of dataset, only four meaningful features have been extracted from the selected EEG channels (Michael J. Fu, 2006). These are: Mean, Std. Deviation, Energy and Entropy.

$$Mean=\frac{1}{N}\sum_{i=1}^{N} P_i$$

$$Std.Deviation=\sqrt{\frac{1}{1-N}\sum_{i=1}^{N}(P_i+Mean)^2}$$

$$Energy=\sum_{i=1}^{N}\left|P_i\right|^2$$

$$Entropy=\sum_{i=1}^{N} P_i^2\log(P_i^2)$$

Using SVM, classification of motor imagery tasks has been performed after extracting features from the de-noised signals of each de-noising algorithms.

E. *Support Vector Machine (SVM)*

Support Vector Machine (SVM) (Durgesh, 2010) is a popular and vastly used tool for classification. In this research, features from selected channels are combined into a group of feature vectors. Firstly, Data is divided into two parts, one is training data and another is for testing. With feature vectors of training data, the model is trained to predict unknown data. Then the model generates a confusion matrix. The equation which training dataset P follows to trains the support vector is defined as this:

$$P=\{(x_i,y_i)\,|\,x_i\in R^k, y_i\in\{-1,1\}\}_{i=1}^{n}$$

Where x_i is an input feature vector which contains k number of attributes. y_i indicates the desired output.

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III. RESULT ANALYSIS

A. Dataset

For this research, a four class motor imagery dataset named BCI Competition 2008 Graz data set A. (M. Tangermann, 2012) is used. This data set consists of EEG data from 9 subjects. Each subject is defined by four classes of motor imagery tasks. Class names with corresponding activities are given below:

TABLE I. Class Distribution of the Dataset

Class	Motor Activity
1	Left Hand Movement
2	Right Hand Movement
3	Legs Movement
4	Tongue Movement

B. Result Analysis and Performance Evaluation

Some visualization of Signal Data after applying the de-noising algorithms are given bellow:

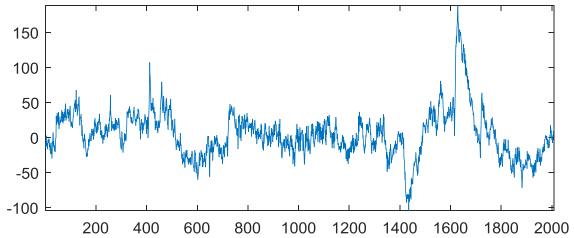

Fig. 3. Class 1 Noisy Signal

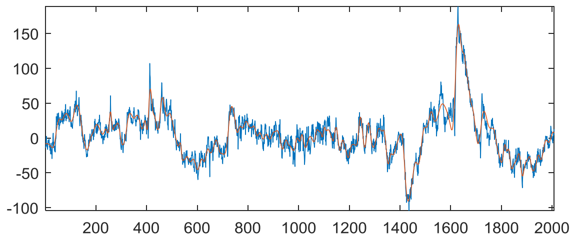

Fig. 4. De-noised signal using EMD (Blue=Orignal Signal, Orange=De-noised Signal)

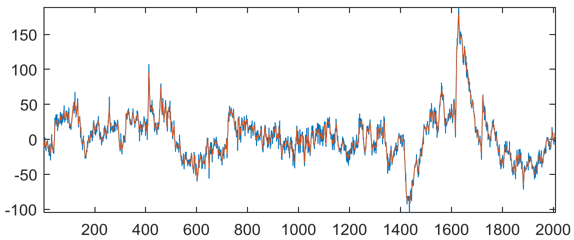

Fig. 5. De-noised signal using DWT (Blue=Original Signal, Orange=De-noised Signal)

TABLE II. Comparison by De-nosing Metrics

Method	MSE	MAE	SNR	PSNR	Cross-correlation
EMD	68.714	6.303	11.717	26.215	0.965
DWT	23.504	3.914	17.088	31.424	0.990

To be a good de-noising method, it needs to possess MSE and MAE as less as it can be and SNR and PSNR as much as it can be. In the case of cross-correlation, it is better when it is close to 1. From the Data table it is clear that DWT is taking better place than EMD in every factors.

Important features have been extracted from the de-noised signals come from each de-noising method. Then training and classification of motor imagery tasks are done with the extracted features and a comparison study is made on those methods based on their accuracy of prediction. The result is as follows:

TABLE III. Comparison by De-nosing Metrics

Method	Accuracy
EMD	71.89%
DWT	85.61%

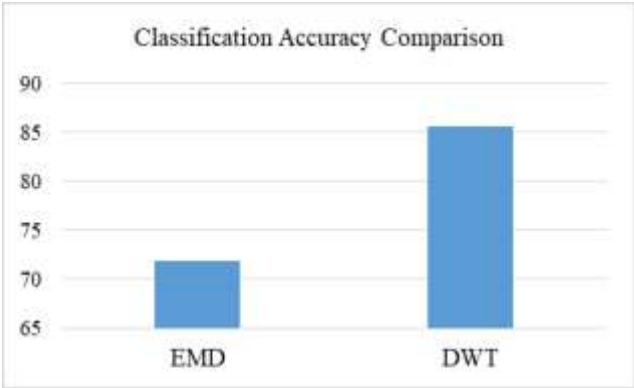

Fig. 6. Classification accuracy for two de-noising algorithms

From the classification using SVM, it is also clear that Discrete Wavelet Transform is dominating the accuracy of Empirical Mode Decomposition.

IV. CONCLUSION

The main objective of this research is to use EEG signals to develop an enhanced recognition of human motor activity. Two major algorithms for the time-frequency domain, i.e. Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) are used for removing artefacts. Finally, the SVM is used in the classification of motor activities based on their statistical characteristics. This paper shows a comparison of DWT and EMD. The comparison takes place in two ways. One is based on important de-noising metrics such as MSE, MAE, SNR, PSNR and cross-correlation and another is based on the accuracy obtained from the classification. In both cases, the Discrete Wavelet Transform (DWT) possesses better results than Empirical Mode Decomposition (EMD).

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