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Effects of Wavelets on Quality of Features in Motor-Imagery EEG Signal Classification

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Abstract— **This paper examines the quality of feature set obtained from Wavelet based Energy-entropy with variation of scale and wavelet type. Here motor imagery of left-right hand movement classification problem has been studied. Elliptic bandpass filters are used to discard unwanted signals and also to extract alpha & beta rhythms. We have implemented wavelet-based energy-entropy with three level of decomposition in combination with ten wavelet types (*Daubechies*). We want to identify the best pair of level of decomposition and wavelet type for EEG based motor imagery classifications. We have verified our study with three classifiers- Naïve Bayes, Multi layered Perceptron and Support Vector Machine. The classifiers performance for best wavelet decomposition level is analyzed using evaluation metrics such as accuracy, F-measure and area under ROC.**

Keywords-EEG; BCI; motor imagery; classification; DWT; energy-entropy; ROC; accuracy; F-measure

I. Introduction

Brain activities can be measured in micro volts electric signals, usually known as “Brain rhythms”. It concentrates on specific brain activities and tries to use them to instruct a computer or an artificial device to do a particular task. These activities are measured by various means (such as Electrophysiological & Hemodynamic BCI techniques) in which non-invasive Electroencephalography (EEG) is widely used because of its portability and cheapness [1,2,3]. BCI provides one of the most important aspects, which is an alternative way of communication through “non-muscular” means. Its prime focus is to provide assistive devices for people with severe disabilities (people unable to perform physical movements). However there are many other applications of BCI. It is the primary aim of the BCI researchers to determine the right intention from the brain activities and reflect them into the desired movement accordingly [4,5]. This particular area in BCI is known as Motor Imagery (MI) movement [6,7]. In this paper we have worked on a data-set comprised of imagery left-right hand movements.

Raw EEG signal has been fed into bandpass filters as a part of pre-processing of the original data. After de-noising, filtered signal is used to apply various combination of discrete wavelet transformation to our desired frequency bands. Extracted feature sets have been passed to classifiers to test their features quality. The flow of our paper is shown in pictorial way in Fig. 1.

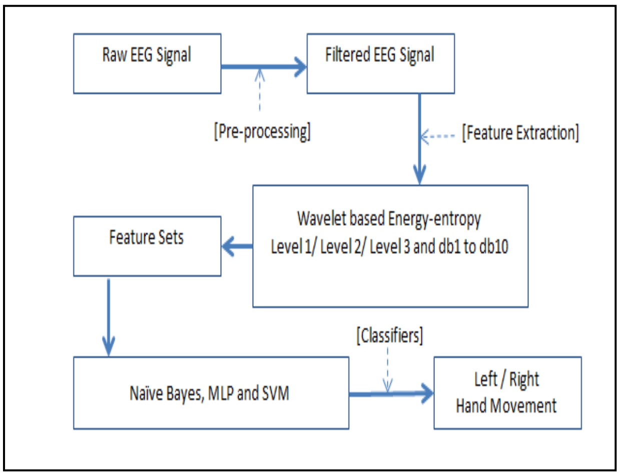

Figure 1. Flow of our study in this paper.

Before features are estimated from the raw EEG signal, filtering technique has been used to de-noise the signal. In simple words, de-noising, feature extraction and classification are performed.

This paper is organized into four sections: section I is about a brief introduction to BCI and motor imagery classification, section II describes the experimental data-set and method used in this paper, section III presents empirical results obtained from our study and provides a broad discussion on it. Finally section IV concludes the paper.

II. Experimental Preparation and Methods

In this paper experimental data (raw EEG signal) has been taken from BCI competition II (dataset III) provided by the Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology, Graz. This data has been used as a benchmark data in the field of EEG based motor imagery classification problem. The details of our used data can be found in [8]. The task aimed to control a feedback bar by means of an imagined left-right hand movement in which the order of left and right cues were random. The EEG data was sampled at 128Hz. Only C3 and C4 are considered for extracting information on left-right hand movement. We have used 140 trials with ten folds cross validation technique for each of the classifiers.

A. Data Preprocessing

As motor imagery signal is concentrated on two frequency bands namely the alpha (8-12 Hz) and the beta (18-25 Hz), so the frequencies higher than this range can be considered as noise. Therefore an elliptic bandpass filter is used to filter in the frequency band of 0.5-30 Hz and also to extract our required frequency bands alpha & beta.

B. Features extraction

In our last work [9] we applied various types of feature extraction techniques for left-right motor imagery hand movement classification. Results compared and concluded that the wavelet based energy-entropy (EngEnt) provides high quality features (table I). Here we have deployed discrete wavelet transformation based feature extraction techniques in an extensive empirical study in order to find out the optimal pair of decomposition level with wavelet type (specifically Daubechies). Three different levels of decomposition and ten different orders of Daubechies have been studied for this paper. It gives us total 30 variants of combination and therefore 30 different feature sets. The said technique is briefly explained below [10-12].

C. Wavelet-based Energy & Entropy

Murugappan et al. introduced this technique, wavlet analysis for feature extraction from EEG signals in the field of emotion classification and later used in motor-imagery classification [13]. Fourier transforms has the drawback of dealing with only the frequency component in the signal. Heisenberg's uncertainty principal states that we can have either high frequency resolution with poor time resolution or vice-versa. On the other hand wavelet is most appropriate for any non-stationary signal like EEG. It cosiders both the frequency range and temporal range at the time of signal processing. The discrete wavelet transforms the signals by decomposing it into coarse approximation and detailed information. It uses hierarchical pyramid algorithm and in each step it halves the actual input signal by 2. The Detail D1 and approximation A1 are obtained from the first high-pass and low-pass filters after transforming the input signal i.e. the first level decomposition. The first approximation is further decomposed and the process is repeated for another two times (i.e. D2 and D3). We have used Daubechies (db) mother wavelet which is varied from order 1 to 10 on filtered signal and the D* features i.e., the detailed coefficients obtained after each level of decomposition for the respective electrodes, were used to estimate the wavelet based energy and entropy by (1) & (2). Previous papers in this motor imagery problem used the detailed cooefficients as the feature sets, but introduction of energy-entropy concept in our last work shows it gives better results and also makes the feature vector length to four only.

$$ENG_l^{C3} = \sum_{n=1}^{2^{S-l}-1} |C_X(l,n)|^2 \quad (1)$$

$$ENT_l^{C3} = -\sum_{n=1}^{2^{S-l}-1} |C_X(l,n)|^2 \log(|C_X(l,n)|^2) \quad (2)$$

The feature vector can be represented a $F_{EngEnt} = [ENG_l^{C3}, ENT_l^{C3}, ENG_l^{C4}, ENT_l^{C4}]$.

TABLE I. DETAILS OF FEATURE VECTORS USED

Features Set Name	Actual Extracted Features Sets	Feature Set Length
EngEnt	Wavelet based Energy-entropy	4

D. Evaluation Metrics

1) Receiver Operating Curve (ROC): A ROC is most widely used way to visualize the performance of a predictor in a binary classifier. Area under the curve (called AUC) is the best way to summarize its performance in a single value [14-15]. ROC plot is done based on True Positive Rate (TPR) in the Y axis and False Positive Rate (FPR) in the X axis. AUC is computed by adding a point (FP/N, TP/P) every time through moving the threshold between 0 to 1.The optimal threshold is that value for which the model will give the highest sensitivity as well as the highest specificity values. In North-west side of ROC space, the distance between top left point i.e. (0,1) and the point on the ROC is the smallest, then the point on the ROC is the best suited 'threshold' where the model exhibits highest sensitivity and specificity both at the same time and hence performs best. On either side of this point either of these measures will decrease with an increment of the value in other.

2) Accuracy: Accuracy is another evaluation metric to measure the quality of a binary classification. In another way the accuracy is the proportion of correct outcomes (both true positives and true negatives) among the total number of instances examined [16].

3) F-measures: In binary classification, the F-measure is a performance evaluation of a test's accuracy. It is the harmonic mean of recall and precision. F-measure is one of the popular statistical analyses metric for model evaluation [17].

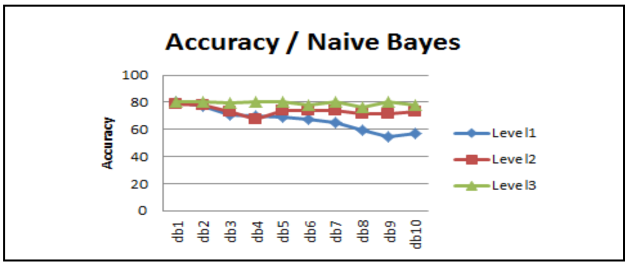

Figure 2. Accuracy plot for Naïve Bayes classifier.

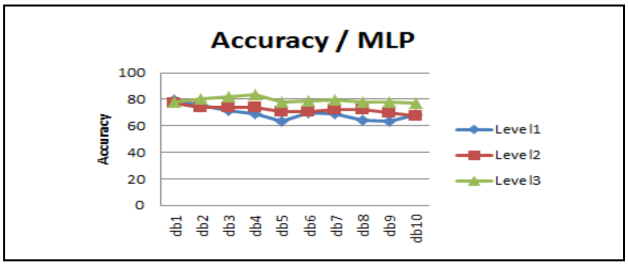

Figure 3. Accuracy plot for MLP classifier.

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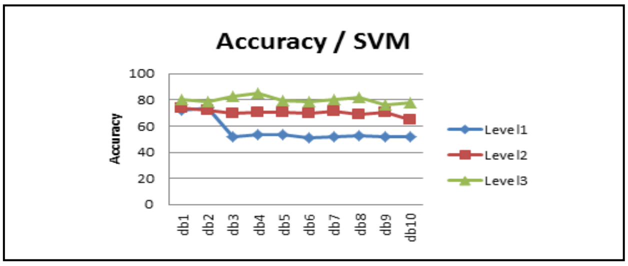

Figure 4. Accuracy plot for SVM classifier.

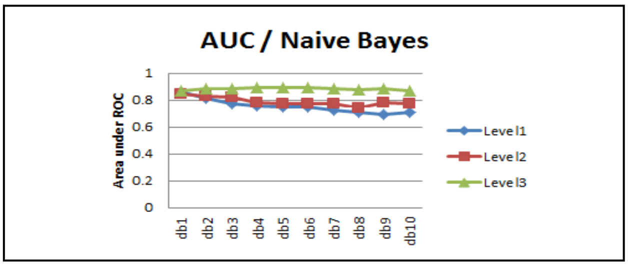

Figure 5. Area under ROC plot for Naïve Bayes classifier.

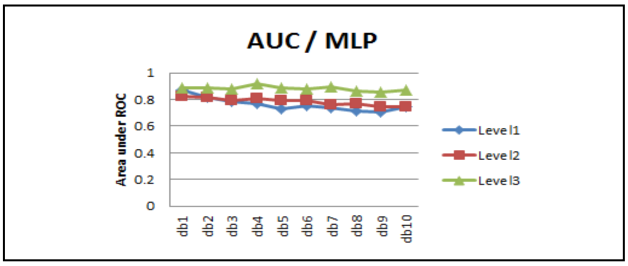

Figure 6. Area under ROC plot for MLP classifier.

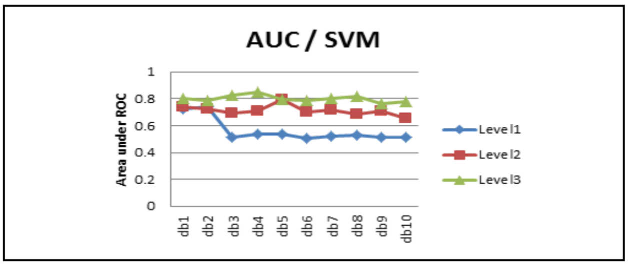

Figure 7. Area under ROC plot for SVM classifier.

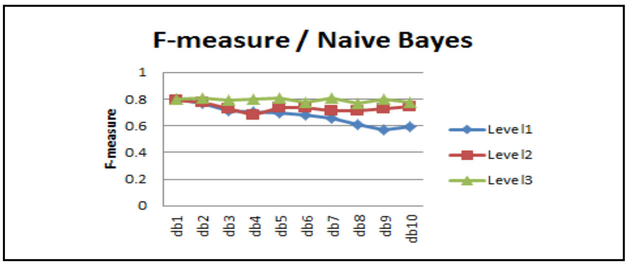

Figure 8. F-measure plot for SVM classifier.

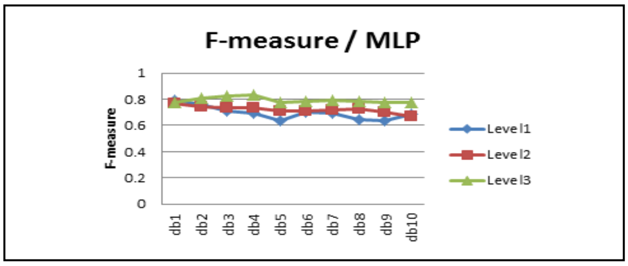

Figure 9. F-measure plot for MLP classifier.

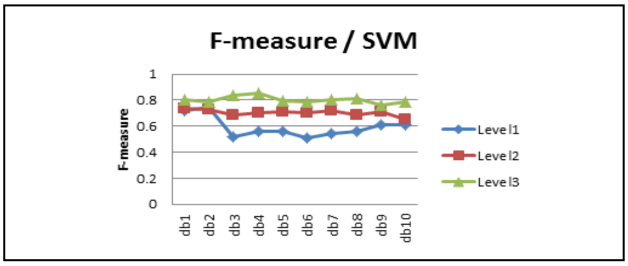

Figure 10. F-measure plot for SVM classifier.

III. Results and Discussions

We have used MATLAB R2014a for feature extraction and WEKA 3.6 classification tool to classify the obtained feature vectors with an Intel Core i5 computer [18]. Three classifiers have been used to measure the significant changes in the feature sets quality. They are Naïve Bayes, Multi Layered Perceptron (MLP) and Support Vector Machine (SVM). Classifiers details are shown in table II. After extensive simulations we plot our results in figures 2 to 10. As we have already mentioned that one evaluation metric cannot completely justify the performance of any classifier, it is advised to incorporate multiple metrics for determining the best performing classifier. We have plotted the performances of the classifiers based on each of the evaluation metrics for all three levels of decomposition. Each plot indicates the mother wavelet of ten different orders (db1 to db10) in x axis and evaluation metrics (accuracy, area under ROC and F-measure) in y axes. Also the green line, red line and blue line signify the third, second and first level of decompositions respectively. In all the figures we observe that the green line stays on the top (of the rest of the lines). Results suggest that wavelet transformation with third level of decomposition and Daubechies of order 4 outperform the other wavelet combinations in terms of features quality.

TABLE II. Types and Variations of Classifiers Used

Classifiers Name used	Kernel function used	
Naïve Bayes	-NA -	
Support Vector Machine	Polynomial	
	Learning rate	**Momentum**
Multi Layered Perceptron	0.7	0.29

IV. Conclusion

In our previous work we observed that the wavelet based (energy-entropy) feature extraction is the most promising among all popular feature extraction techniques. Our results propelled us to examine the wavelet based feature extraction techniques in a rigorous way. As we already stated in the abstract that our aim in this paper is to validate best wavelet decomposition level (i.e. 3) in combination with wavelet type (db4). Presently in signal processing related literatures it is suggested that third level decomposition and Daubechies wavelet of order 4 is the best suited wavelet transformation combination for high quality features. It has not been verified in the field of BCI, particularly in the EEG signal based applications. Extracted features obtained from the 30 variants of wavelet combinations (3 levels of decomposition and 10 orders of Daubechies wavelet), are fed into three classifiers. It is to examine the effects of wavelets on the quality of features from the motor-imagery EEG signal. However this paper is not made to compare the classifications performance, but here classifiers are used to measure the quality and relevance of the extracted features through its evaluation metrics such as accuracy, area under ROC and F-measure. In Fig. 2 to 10, we observe that the features extracted from level three decomposition performs better than level 2 and level 1 for all wavelet orders (i.e. db1,…db10). Again if we find the peak from each of the plots, the Daubechies wavelet of order 4 provides the best features in all level of decompositions (table III).

In future we will implement other wavelet types and extend our work to analyze other wavelet based feature extraction methods like Root Mean Square (RMS) or their combinations.

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TABLE III. RESULTS OF ENERGY-ENTROPY AT DECOMPOSITION LEVEL 3

Wavelet order (Daubechies)	Evaluation Metrics	Classifier Names		
		Naive Bayes	MLP	SVM
Db1	Accuracy (%)	80.0000	77.8571	80.0000
	F-measure	0.800	0.779	0.800
	ROC Area	0.873	0.887	0.800
Db2	Accuracy (%)	80.7143	80.7143	78.5714
	F-measure	0.807	0.809	0.790
	ROC Area	0.887	0.888	0.786
Db3	Accuracy (%)	79.2857	82.1429	82.8571
	F-measure	0.793	0.824	0.834
	ROC Area	0.887	0.878	0.829
Db4	Accuracy (%)	80.0000	83.5714	85.0000
	F-measure	0.801	0.837	0.853
	ROC Area	0.897	0.917	0.850
Db5	Accuracy (%)	80.7143	77.8571	79.2857
	F-measure	0.807	0.779	0.796
	ROC Area	0.893	0.885	0.793
Db6	Accuracy (%)	77.8571	78.5714	78.5714
	F-measure	0.779	0.786	0.787
	ROC Area	0.890	0.878	0.786
Db7	Accuracy (%)	80.7143	79.2857	80.0000
	F-measure	0.807	0.795	0.803
	ROC Area	0.886	0.894	0.800
Db8	Accuracy (%)	76.4286	77.8571	81.4286
	F-measure	0.765	0.780	0.816
	ROC Area	0.878	0.867	0.814
Db9	Accuracy (%)	80	77.8571	76.4286
	F-measure	0.800	0.779	0.765
	ROC Area	0.882	0.857	0.764
Db10	Accuracy (%)	77.8571	77.1429	77.8571
	F-measure	0.779	0.772	0.784
	ROC Area	0.870	0.872	0.779

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