Study of Wavelet-Based Performance Enhancement for Motor Imagery Brain-Computer Interface

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***Abstract*—To enhance the reliability of motor imagery based brain-computer interface, we present a study that considers subject-based optimization of feature extraction and classification. In particular, wavelet-based feature extraction performed on different bands was optimized over available selections of wavelet family, length and number of decomposition levels. Likewise, the classification step considers three general families of classifiers whose parameters are optimized in a similar manner. Such optimization was performed for each subject whereby processing parameters are selected based on the best performance obtained in the training session. We report the results obtained from applying this approach to the BCI competition 2008 dataset 2b (Graz) and demonstrate that such optimization provides results that outperform previous methods.**

Keywords- Brain-computer Interface; EEG; Wavelet Transform.

I. INTRODUCTION

The brain-computer interface (BCI) is an artificial pathway that allows a patient who is strictly disabled by neuromuscular disorders such as the amyotrophic lateral sclerosis to communicate effectively with the society as well as control devices like wheelchair [1]. Patients with locked-in syndrome who could control only their eye muscles or fully paralyzed patients that are still cognitively aware can take advantage of BCI technology to find a useful alternative to their impaired speech or motor activity to communicate directly using their brain activity. The aim of BCI is to train the patient and the computer to communicate through cognitive commands in the form of designated electroencephalography (EEG) signals from the brain and at particular times. BCI can also be defined as an artificial Central Nerves System pathway output [2].

Among the most popular BCI techniques is the one based on motor Imagery, which has received a lot of attention from many groups. Here, we focus on the research work done on the interesting BCI competition 2008 dataset 2b (Graz). In Ghahiri *et al.*, the authors extracted the features by windowing the EEG signals and taking the common spatial pattern for each time segment. The multiclass diagonalization problem was solved by the One-Versus-Rest (OVR) algorithm that breaks a multiclass problem into two classes, further applying linear discriminant analysis (LDA) as a classifier and got an averaged kappa value 0.61 of 9 subjects [3]. Mingai *et al.*, considered the motor Imagery based EEG signal as a nonlinear time varying and nonstationary signal, therefore, they proposed a novel feature extraction method that is based on the locally linear embedding (LLE) algorithm and discrete wavelet transform (DWT). LLE was applied to extract the nonlinear components and the DWT to calculate their statistics to gain the time-frequency features. These two features were combined serially and the backpropagation neural networks (BPNN) was optimized by the genetic algorithm and applied for classification [4]. Ang *et al.* proposed to employ a common spatial pattern algorithm on the multi-frequency bands. Their filter bank method for common spatial pattern (FBCSP) was the winner of the BCI competition 2008 for the dataset 2b [5]. Delgado Saa and Cetin. proposed a classification approach based on hidden conditional random fields (HCRFs) to extract features based on autoregressive modeling of the EEG signals and computing the power spectrum. Their approach outperformed the winner of the Graz 2008 for the dataset 2b [6]. Sayed *et al.* proposed a method that addresses nonlinear dynamics of the EEG signals whereby the phase space trajectory was modeled based on affine invariant moment and a new distance series transform showing improvement over previous work in most subjects [7].

In this work, we aim to enhance the reliability of BCI motor imagery by studying subject-based optimization of feature extraction and classification. Wavelet-based feature extraction performed on different bands of the EEG signals is optimized over available selections of the wavelet family, length and number of decomposition levels. The classification step considers three general families of classifiers and their parameters are optimized as well. Such optimization is performed for each subject whereby processing parameters selected based on the best performance obtained in the training session. We obtain better performance compared to other methods on the results of the BCI competition 2008 dataset 2b (Graz).

II. METHODOLOGY

A. Dataset

The dataset considered in this study is the BCI Competition 2008 Graz dataset 2b acquired from 9 subjects [8]. The volunteers underwent five sessions; three sessions for training and two sessions for evaluation. The EEG signals were collected from three bipolar channels (C3, Cz and C4) and sampled at 250 sample/s. The signals were notch filtered at 50 Hz to remove line power noise and bandpass-filtered between 0.5 – 100 Hz.

The cue based paradigm employed in the experiments comprised binary classification of motor Imagery based on left or right hand imaginary movement. The paradigm was designed as follows. A fixation cross appeared for 3 seconds interval with a warning beep sound after 2 seconds. Then the imagery cue (left/right arrow) appeared for 1.25 seconds. After that, an imagery period of 4 seconds is allowed. Finally, at the end of each trial there was a short break for 1.5 seconds. Two sessions out of five were acquired on two different days within two weeks. Each session included six runs with ten trials for each class. This provided 120 trials per session.

B. Preprocessing

To spatially localize the neural activation, we selected bipolar electrodes C3 and C4 located in the both right and left hemispheres within the motor cortex area. The raw EEG signals were band-pass filtered using constrained least squares algorithm for designing finite impulse response filter within the delta (0.5 – 3 Hz), alpha (7 – 14 Hz), beta (18 – 38 Hz) and gamma (45 – 95 Hz) bands. In order to eliminate the transient effects at the beginning of the filtered signal, zero phase filtering technique was used.

C. Feature Extraction

In order to capture the signal differences between the two classes of motor imagery, wavelet analysis offers a multiscale view of the variations within each and hence allows for more accurate detection of such difference. Since selection of basic wavelet family and size has generally been known to affect the analysis, a broad study that included several wavelet families at different sizes was conducted in this work. Five wavelets families including Haar, Daubechies 1-10, symlets 1-5, Coiflets 1-5, and BiorSplines 1.1-5 and 2.2-8. Furthermore, five levels of decomposition were used for each type. The feature set includes the wavelet coefficients for detail and approximation outputs for each level as well as the energy. Both the log variance of percentage and energy for each.

The feature extraction from different wavelets at all levels was repeated for all filtered signals in all frequency ranges with/without denoising as described in the preprocessing step. The resultant feature vectors served as the inputs to the classification step.

D. Classification

The feature vector sets from each of the different combinations of preprocessing parameters and wavelet decompositions for three training sessions were used to train

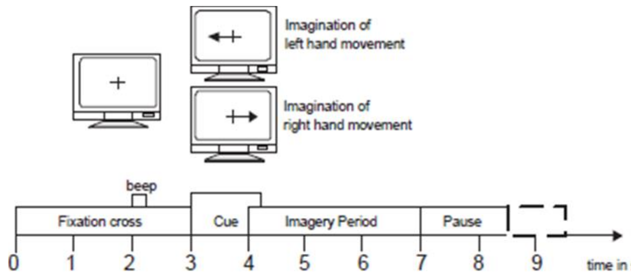

Figure 1. Experimental paradigm of Graz dataset 2b [8].

three classifiers based on three general families of classifiers. Namely, support vector machine (SVM) [9], regularized linear discriminant analysis (rLDA) [10], and logistic regression [11].

Each subject was trained separately to account for subject variability. Since experimental sessions were likely to be conducted under different conditions, training was repeated with all combinations of the three training sets to minimize the experimental variance. Also, to optimize the process further, the best set of preprocessing/feature extraction/classification parameters that yielded the best training outcome was selected to perform the testing phase. The performance of the three classifiers after training with the optimal set of parameters was assessed using the remaining two testing sessions for each subject. In Fig. 2, a summary of the processing combinations considered in this study that were obtained by applying all alternatives for each step resulting in 1680 combinations (e.g., 4time Intervals, 4 frequency bands, 5 wavelets families, 21 sub-wavelets and 5 wavelets levels).

III. RESULTS AND DISCUSSION

The result of the Graz dataset 2b are presented in Table 1. Each row presents the best results obtained using the optimal set of processing parameters for a particular subject along with a listing of the optimal parameters used for that particular subject. The average accuracy obtained was 83.81% while the average kappa value was 0.68.

In order to put the results in perspective, Table 2 presents the best results for the dataset used including the competition winners and two more recent studies that show improvement over the competition winners. The comparison metric used in Table 2 is based on the Cohen-kappa since it was the metric of choice for this particular dataset in the competition. This ensured the availability of its values in all research papers using this dataset. Table 2 shows that the results presented in this study outperforms all previous studies with a kappa value of 0.68.

The results in this study outline the variability of results based on the processing parameters including number and conditions of the training sessions, time window used to extract the motor imagery changes, frequency band used within the obtained signals, wavelet decomposition parameters, as well as classification parameters. The results also indicate that each subject exhibit optimal performance at different parameters and therefore this emphasizes the importance of customizing the processing parameters to best fit each subject.

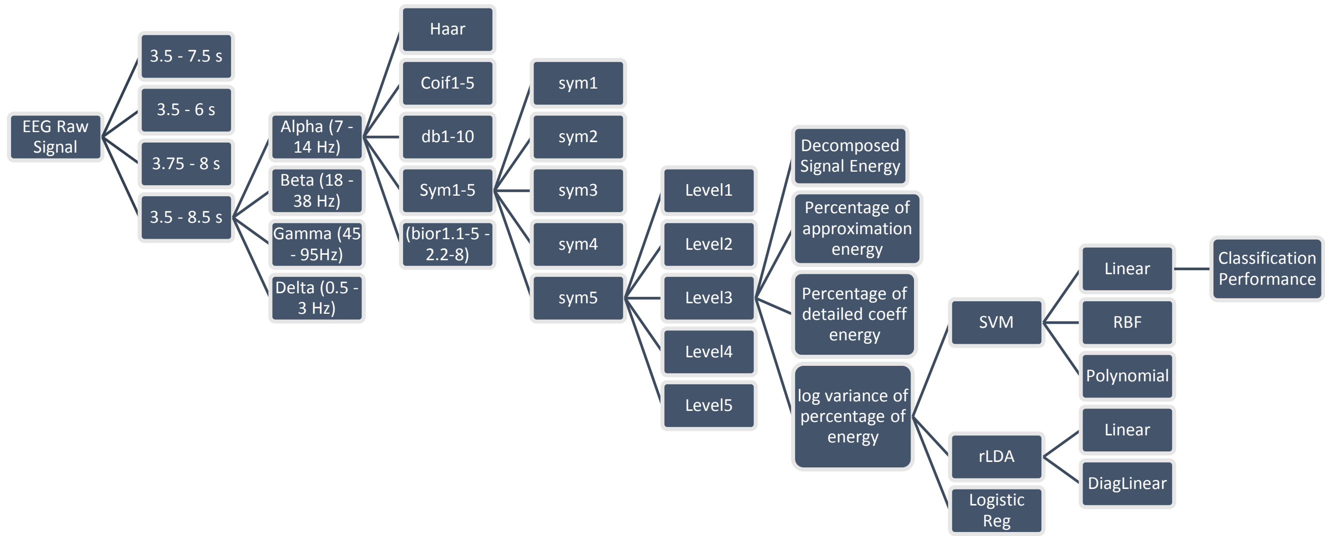

Figure 2. Block diagram for the proposed study

In Fig. 3, the delta rhythm shows more contribution in the complex neural activation of motor imagery compared to the alpha band for the subject 5. Some researcher found that the delta rhythm would contribute in motor related cortical potentials (MRCPs) that start firing by movement intention. Furthermore, the gamma rhythm behaves opposite to the beta rhythm where increasing the activation of beta rhythm on C3 decreases the activation of gamma rhythm on the same electrode. Therefore, this study takes both delta and gamma rhythms in consideration to reduce the complexity of endogenous neural activation.

The average processing time for the proposed optimized methods was estimated to be 29 ms on a modest processing platform comprising a laptop with Intel® Core™ i5 2.5 GHz processor and 8 GB RAM under Windows 7 operating system. The code was developed using MATLAB 2016b. Once optimization of the processing parameters is done, the optimized technique will be able to run in real-time.

IV. CONCLUSIONS

In this work, we presented a study of subject-based optimization of wavelet-based feature extraction and classification. Such optimization was performed for each subject whereby processing parameters are selected based on the best performance obtained in the training session. We reported the results obtained from applying this approach to the BCI competition 2008 dataset 2b (Graz) and demonstrated that such optimization provides results that outperform previous methods.

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TABLE 1. PROPOSED SUBJECT-OPTIMIZED PERFORMANCE FOR BCI COMPETITION 2008 DATASET 2B

Subject	Training sessions	Feature Extraction					Classification	Performance	
		Band	Time window	Wavelet type	Wavelet level	Sample/ Feature	Classifier	Accuracy	Kappa
1	S1-S2	All	3.5 - 8.5 s	bior1.1	1	240/32	SVM-linear	81.25	0.63
2	S3	Alpha-delta	3.5-7.5 s	coif5	2	160/24	Logistic regression	64.29	0.29
3	S2-S3	All	3.75 -5.5 s	bior1.5	3	280/48	Logistic regression	63.44	0.27
4	S3	Alpha	3.5 -5.5 s	bior1.5	3	160/2	SVM-linear	97.2	0.94
5	S3	delta-beta-gamma	3.5 - 7 s	sym1	7	160/60	SVM-linear	95.94	0.92
6	S1-S3	alpha	3.75 - 8.5 s	db1	3	280/10	SVM-linear	90.31	0.81
7	S1-S3	alpha	3.5 - 7 s	db2	5	280/16	SVM-linear	79.37	0.59
8	s3	alpha	3.5 - 7.5 s	bior2.4	3	160/12	SVM-linear	94.06	0.88
9	S1-S3	alpha-beta	3.5-8.5 s	db2	3	280/24	SVM-linear	88.44	0.77
Average								**83.81**	**0.68**

TABLE 2. COMPARISON OF METHODS BASED ON KAPPA VALUE FOR BCI COMPETITION 2008 DATASET 2B

Subject	Sayed *et al.* [7]			Ang *et al.* [5]	Delgado Saa and Cetin [6]	Proposed
	Moment Invariants	Distance Series	Combined	FBCSP	HCRFs	
1	0.4	0.43	0.39	0.4	0.56	0.63
2	0.32	0.29	0.31	0.21	0.24	0.29
3	0.27	0.26	0.28	0.22	0.18	0.27
4	0.95	0.95	0.95	0.95	0.95	0.94
5	0.59	0.85	0.83	0.86	0.93	0.92
6	0.54	0.54	0.48	0.61	0.72	0.81
7	0.59	0.6	0.62	0.56	0.51	0.59
8	0.85	0.9	0.9	0.85	0.8	0.88
9	0.71	0.66	0.7	0.74	0.71	0.77
Average	0.58	0.61	0.61	0.6	0.62	**0.68**

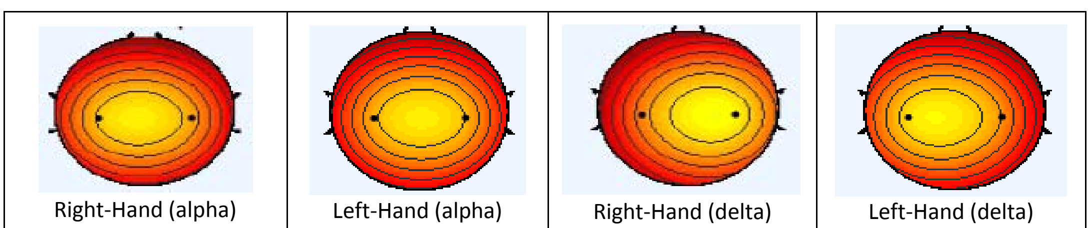

Figure 3: Topographical map of C3 and C4 during Right and Left hands MI of two frequency bands. (subject 5)