Neural Network-based Three-Class Motor Imagery Classification Using Time-Domain Features for BCI Applications

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***Abstract*—Many studies have reported the usefulness of motor imagery (MI) electroencephalogram (EEG) signals for Brain Computer Interface (BCI) systems. MI has been broadly characterized by the average of event-related changes of brain activity at specific frequency bands; but, temporal features of EEG have rarely been considered to identify different mental states of BCIs' users. Additionally, complex classification techniques may have been proposed to enhance the accuracy of system but they may cause a notable delay during online applications. This paper investigated the application of neural network-based algorithms to classify three-class MIs by utilizing EEG time-domain features. Integrated EEG (IEEG) and Root Mean Square (RMS) features were extracted from EEG signals. Then, Multilayer Perceptron and Radial Basis Function Neural Networks were employed to classify the features. The discrimination ratio of such features were examined and compared through different classifiers. Moreover, the robustness of classifiers was investigated and compared. The results of this study indicated that RMS was more capable than IEEG for characterizing MI movements and RBF was more accurate and faster than MLP. The effectiveness of IEEG and RMS features and the performance of MLP and RBF classifiers were compared with Willison Amplitude (WAMP) feature and support vector machine (SVM) classifier respectively. This study proved that WAMP and SVM were more efficient for classification of MI tasks in both terms of accuracy (88.96%) and training time (0.5 second); however, considerable difference was not observed since RBF performed as fast as SVM with only about 3% less accuracy.**

Keywords—Brain Computer Interface; Electroencephalogram; Motor Imagery; Time-Domain Feature; Classification.

I. INTRODUCTION

Brain Computer Interface (BCI) aims to create a new communication pathway that can translate sever disabled intentions into control signals to drive a rehabilitation device or a neuroprosthesis [1]. Various BCI systems using EEG signals have been introduced among which Motor Imagery (MI)-based is one of the most promising [2] especially for paralyzed patients and asynchronous BCIs [3].

An efficient pattern recognition-based BCI system includes several key components where feature extraction and classification are the most challenging ones. EEG signals are non-stationary and therefore extraction of accurate and discriminative features is necessary to represent the underlying mental tasks. Moreover, features have a direct impact in determining the performance of a classifier; thus, inaccurate features may lead to poor classification ratio and computational complexity [4]. In EEG-based BCIs, feature extraction methods are categorized into time-domain, frequency-domain, time-frequency analysis, and spatial-domain methods. Autoregressive (AR) modeling is the most commonly used in the time-domain analysis of MIs. Quantification of Event-Related Synchronization/ Desynchronization (ERS/ERD) phenomenon is one of the popular techniques for characterizing EEG power spectra. Morlet Wavelet transform, Empirical Mode Decomposition (EMD), Hilbert-Huang Transform (HHT), short-term Fourier transform (STFT) are examples of Time-Frequency methods that have been proposed in this area. Spatial feature extraction method includes Principal Component Analysis (PCA), Independent Component Analysis (ICA), Common Spatial Pattern (CSP) and Surface Laplacian Derivation (SLD). In addition to feature extraction method, classification algorithm also plays a dominant role in achieving reasonable performance for MI-based BCI systems. Numerous linear and non-linear algorithms have been suggested in this area among which Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K-Nearest Neighbor [5] are widely used.

Literature reviews indicate that researchers are still looking for more effective and robust techniques in order to boost the system performance by employing more complex feature extraction and classification algorithms regardless of how much computational cost may be added to overall system. Nonetheless, a practical and effective BCI system requires a reliable trade-off between its outputs accuracy and interface complexity. Considering this fact, recently, several simple time-domain features Mean Absolute Value (MAV), Maximum value (MAX), Simple Square Integral (SSI), Willison Amplitude (WAMP), Waveform Length (WL) were evaluated

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for discriminating four MI movements by means of SVM and Fuzzy C-means (FCM) classifiers [6]. The results showed that, 85.07% accuracy was achieved while using WAMP features and SVM classifier; however, the computational load of the proposed method was not reported [6].

In this paper we have proposed a new BCI in order to achieve reliable performance indices in both accuracy and complexity terms. Hence, Integrated EEG (IEEG) and Root Mean Square (RMS) methods were applied to extract features for characterizing three-class MI task. Conventional Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks were employed separately for classification purpose. This study investigated the effectiveness of IEEG and RMS features and the results were compared with WAMP, approved as an effective feature [6]. Moreover, the classification performance of the two suggested classifiers was compared with SVM in terms of classification accuracy and training time.

The rest of the paper is organized as follows. In the next section, EEG data collection, preprocessing (including filtration and data segmentation), feature extraction and classification are described. The results obtained from several experiments of this study are discussed in section 3. Finally, a brief summary and future work are presented in last section.

II. Methods and Materials

A. General Block Diagram

The block diagram of the method proposed in this paper is depicted in Fig. 1. The whole procedure consists of the following steps which have been explained throughout the paper: data acquisition including subject preparation, system setup, and recording sessions; EEG filtering and data segmentation; feature extraction using RMS and IEEG methods; classification by MLP and RBF neural networks; system evaluation including features and classifiers assessment and a comparative study.

B. Data Acquisition

In this experiment scalp EEG signals were recorded from ten healthy subjects (right-handed, aged 25-34 years) via g.tec device through three channels C3, Cz and C4 (placed based on the international 10/20 system) with a 512 Hz sampling rate. Reference electrode was located on the left mastoid, behind the ear and the ground electrode was placed at FPz, near the forehead. In order to envelope the significant spectrum of MI tasks, EEGs were band-pass filtered (0.5 and 30 Hz) and power line inference noises (50 Hz) were removed by a notch filter.

The subjects sat on a comfortable arm chair with closed eyes for 2 minutes in order to relax. Noncue-based (asynchronous) recording scheme was considered in this study while subjects were asked to continuously imagine the movements of left hand, right hand, and tongue in three separate runs for one minute with 5 minutes rest between. No feedback was given to the subjects during the execution of MI movements. Filtered EEGs were segmented into non-overlapped windows with 256 milliseconds length and then got prepared for feature extraction.

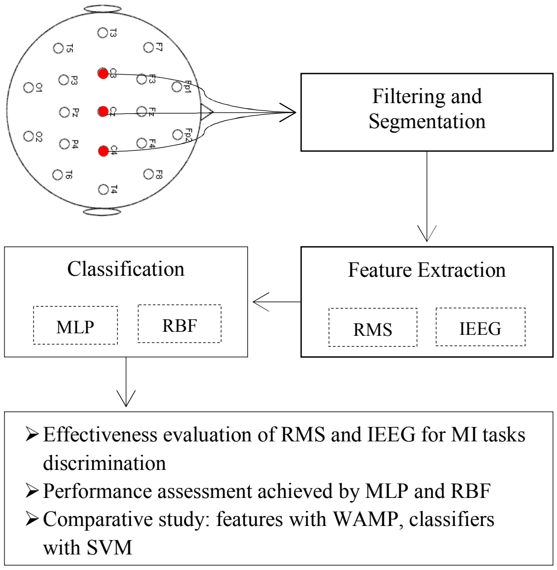


Fig. 1. General Block Diagram

C. Feature Extraction

As stated before, one of the most challenging issues in designing BCI is extracting the relevant EEG features. For a classifier, more discriminative and informative features may lead to better discrimination ratio between different classes of MI movements. On the other hand, suitable feature should be easy to compute to prevent the increase in computational cost of BCI system. Time-domain features have been proposed especially when a signal can be modeled as a Laplacian and Gaussian random process. These features are computed based on the signals' amplitudes, and they require no transformation or complex calculation. Various types of such features have been widely used and investigated on different bio-signals and applications [6-8]. In this study, time-domain features IEEG and RMS were computed and extracted from the segmented EEGs. RMS is modeled as amplitude modulated Gaussian random process while IEEG estimates the power of EEG signals (equations (1) and (2)). The effectiveness of these features on MI movement classification was investigated in this study.

$$RMS_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

$$IEEG_t = \sum_{i=1}^{N} |x_i| \tag{2}$$

where t is the current segment, N is the length of the segment, x_i is the current point of signal and i is the index of the current point.

In order to make more separable feature vectors, log transform was employed on extracted features to spread the concentrated features when considering the highly scattered features [9].

D. *Classification*

BCI systems require fast and accurate classifier to translate the extracted features into a control signal. Due to the fact that more robust techniques deliver better performance, advanced non-linear algorithms have been suggested. However, these methods may need much more time to train the features compared with conventional classifiers. Since one of the major goals of this paper is to provide a performance that can make a reliable trade-off between high accuracy and low computational cost; MLP and RBF neural networks have been applied to examine their robustness for classification of MI tasks while being trained by time-domain features. Furthermore, the effectiveness of the proposed features has been assessed by these classifiers.

MLP is a feed-forward artificial NN which employs the supervised learning Backpropagation (BP) algorithm for network training. RBF is a mixture of instance-based and probabilistic artificial NN approaches. It is a three layer NN with spatially localized kernel functions (radial basis functions) as activation functions in the hidden layer [10]. The output of the network is a linear combination of RBFs of the inputs and neuron parameters. In our study, the input layer of MLP and RBF network included 3 neurons (equal to feature vector dimensions). In the hidden layer, this number was selected manually in each run so as to reach the best performance. The number of neurons in the output layer was the same as the number of classes in the training data set. For the MLP network, the saturating linear activation function was also considered. In the RBF network, neuron parameters known as spread of radial basis functions were adjusted manually for each run to gain the highest performance. In order to construct the NN, each feature set was shuffled and divided into 70% and 30% data sets for training and testing respectively.

III. Results and Discussion

In this section the results achieved from the experiments are discussed. For the purpose of evaluation, classification accuracy and training time were considered as the major metrics. The former highlights the final performance of the test data sets while the latter elucidates the computational load during the training stage.

Table 1 presents the classification accuracy and the training time by MLP and RBF while using RMS and IEEG features averaged over all subjects. The results obtained by MLP indicated that, RMS delivered a higher accuracy (82.50%) whereas there was no considerable difference in the training time using each feature. RMS also led to a higher accuracy in RBF classifier and required less training time in comparison with IEEG. Accordingly, RMS provided a higher discriminative ratio for classification of the three MI movements. Besides, RBF outperformed MLP in terms of accuracy and training time for both features.

TABLE I. Classification accuracy and training time achieved by MLP and RBF using RMS and IEEG features averaged over all subjects

Classifier	Feature	Accuracy (%)	Training Time (sec)
MLP	RMS	82.50±7.73	3.30±1.30
	IEEG	81.07±8.01	3.20±1.16
RBF	RMS	84.94±6.73	0.53±0.05
	IEEG	81.52±8.92	0.78±0.25

The results of this study also were compared with the proposed methods in [6] where SVM and WAMP were introduced as the robust classifier and feature respectively. WAMP feature led to a higher accuracy while being classified by all classifiers (Fig. 2a). Moreover, SVM outperformed MLP and RBF for classification of IEEG and WAMP. Here, the highest accuracy was 88.96% for classification of WAMP using SVM. On the other hand, as shown in Fig. 2(b), RBF and SVM performed very fast (less than a second) for training all features whereas MLP required more time (~3-4 seconds). In addition, standard deviations (vertical lines within the bars) showed that, the training time alterations over all subjects were more consistent for RBF and SVM compared to MLP. This figure also indicates that the lowest time was consumed for training SVM classifier with WAMP features (0.5 second). Finally, the results of this study supported the robustness of SVM and WAMP again for distinguishing the different MI movements.

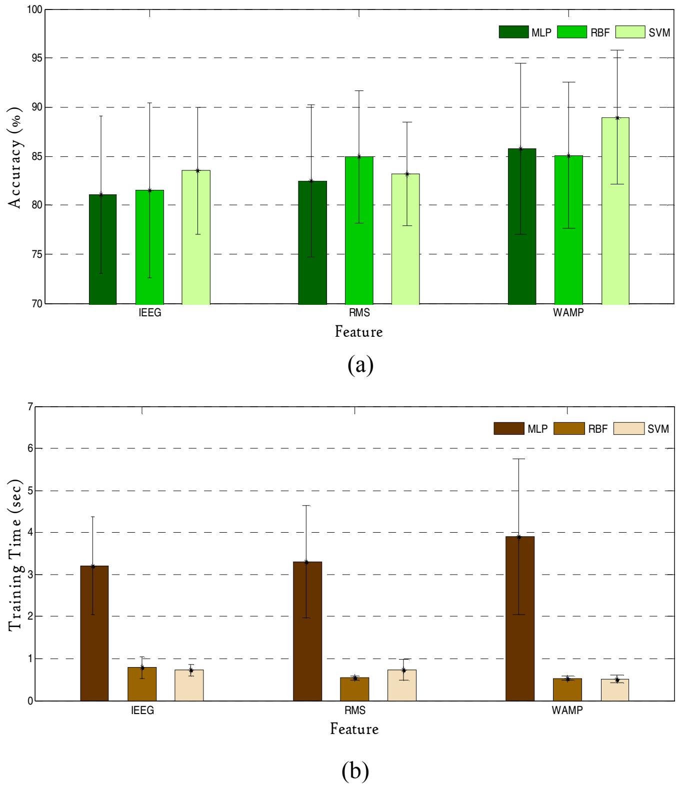
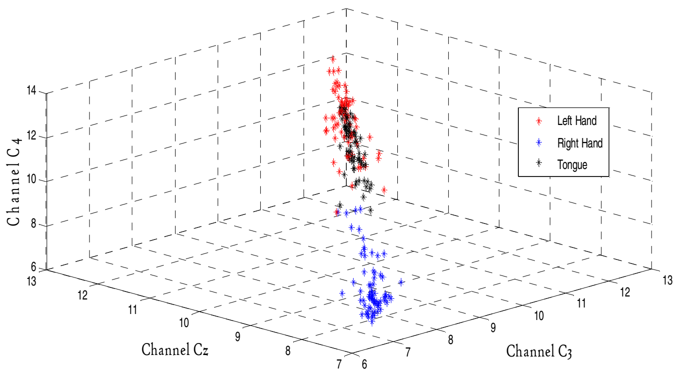
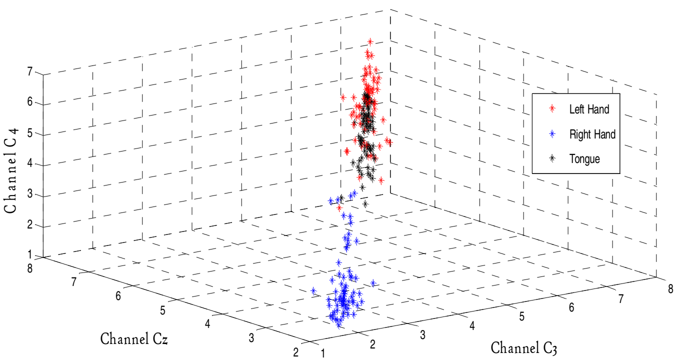


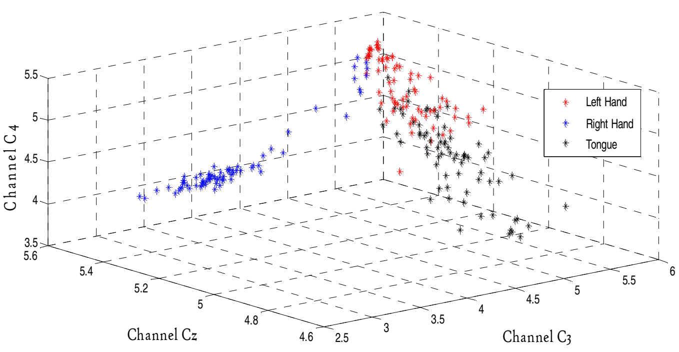
Fig. 2. Results achieved by all classifiers by considering IEEG, RMS, WAMP features separately averaged over all subjects; (a) Classification accuracy; (b) Training time



(a)



(b)



(c)

Fig. 3. Distribution of features in feature space related to a subject (a) IEEG, (b) RMS, (c) WAMP

Distribution of IEEG, RMS and WAMP training features in feature space for one subject are visualized in Fig. 3. As can be seen, RMS and IEEG features discriminated the MI tasks in similar manner while WAMP provided more clear separation which resulted in better accuracy after classification. The common point in all figures is that, features akin to the left hand and tongue were more overlapped which caused more misclassification between these classes. Moreover, MI of right hand movements seemed to be more separable from other tasks.

IV. Conclusion

This paper proposed and evaluated the application of MLP and RBF to classify three mental tasks while using IEEG and RMS time-domain features. Here, it has been shown that employing time-domain features are plausible for motor imaginary applications that simultaneously require rich information content and low computational cost. In addition, RBF was more accurate and faster than MLP while using RMS feature. In comparison with WAMP, it was illustrated that WAMP was more suitable for characterizing MI-EEG signals since it provided more discriminative information for each MI task. Furthermore, SVM outperformed MLP and RBF thus it is recommended in BCI research in which a reasonable trade-off between accuracy and speed are required; however, more robust classifiers should be studied in future works.

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