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EEG-Based Classification of Imagined Fists Movements using Machine Learning and Wavelet Transform Analysis

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***Abstract*—Electroencephalography (EEG) signals represent the brain activity by the electrical voltage fluctuations along the scalp. In this paper, we propose a system that enables the differentiation between imagined left or right fist movements for the purpose of controlling computer applications via imagination of fist movements. EEG signals were filtered and processed using a hybrid system that uses wavelet transform analysis and machine learning algorithms. Many Daubechies orthogonal wavelets were used to analyze the extracted events. Then, the Root Mean Square (RMS) and the Mean Absolute Value (MAV) were calculated to the wavelet coefficients in two detail levels. Support Vector Machines (SVMs) and Neural Networks (NNs) were applied to the feature vectors and optimized by carrying out an intensive learning and testing experiments. Optimum classification performances of 84.5% and 82.1% were obtained with SVMs and NNs, respectively. Compared with the related research work reported in the literature, our system showed a good performance for the classification of fists movements, which enables the control of many computer applications via imagination.**

***Keywords*—BCI, Data Mining, Machine Learning, SVMs, NNs, DWT, Feature Extraction**

I. Introduction

Brain-Computer Interface (BCI) or Brain-Machine Interface (BMI) is a device that enables the use of the brain's neural activity to communicate with others or to control machines, artificial limbs, or robots without direct physical movements [1-4]. As computerized systems are becoming one of the main tools for making people's lives easier and with the ongoing growth in the BCI field, it is becoming more important to understand brain waves and analyze EEG signals. Electroencephalography (EEG) is the process of measuring the brain's neural activity as electrical voltage fluctuations along the scalp as a result of the current flows in brain's neurons [5]. The brain's electrical activity is monitored and recorded, in typical EEG tests, using electrodes that are fixed on the scalp [6]. BCI captures EEG signals in conjunction with a specific user activity then uses different signal processing algorithms to translate these records into control commands for different machine and computer applications [7]. Vidal [8] proved that a user's intent could be effectively represented by signals recorded from brain activity.

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BCI was known for its popular use in helping disabled individuals by providing a new channel of communication with the external environment and offering a feasible tool to control artificial limbs [9]. Grabianowski [10] described a variety of BCI applications including the control of devices using the translation of thoughts into commands in video games and personal computers. BCI is a highly interdisciplinary research topic that combines medicine, neurology, psychology, rehabilitation engineering, Human-Computer Interaction (HCI), signal processing and machine learning [11].

In [12] we proposed a system that could efficiently discriminate between executed left and right fist movements. The current research work is an extension for our studies to focus on imagined fists movements by analyzing EEG signals recorded during a large number of experiments for 20 different subjects. The Daubechies Wavelet coefficients were calculated and then all the possible feature candidates were extracted and used in the training/testing and optimization experiments of SVMs and NNs.

II. Literature Review

The translation approach used to transform EEG signal patterns into machine commands reflects the strength of BCI applications. In [13], the authors recorded EEG signals for three subjects while imagining either right or left hand movement based on a visual cue stimulus. They were able to classify EEG signals into right and left hand movements using a neural network classifier with an accuracy of 80% and concluded that this accuracy did not improve with increasing number of sessions. Sepulveda [14] used features produced by Motor Imagery (MI) to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8-12Hz and beta: 13-30Hz) were mapped into right and left limb movements. In addition, they used similar features with MI, which are the Event Related Desynchronization and Synchronization (ERD/ERS) comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state.

The combination of ERD/ERS and Movement-Related Cortical Potentials (MRCP) was proven to improve the classification of EEG signals as this offers an independent and complimentary information [12, 15]. The authors of [16] presented an approach for the classification of single trial MRCP using a discrete dyadic wavelet transform and Support Vector Machines (SVMs) and they provided a promising classification performance. A single trial right/left hand movement classification is reported in [17]. The authors analyzed both executed and imagined hand movement EEG signals and created a feature vector consisting of the ERD/ERS patterns of the mu and beta rhythms and the coefficients of the autoregressive model. Artificial Neural Networks (ANNs) is applied to two kinds of testing datasets and an average recognition rate of 93% is achieved. A three-class BCI system was presented in [18] for the translation of imagined left/right hands and foot movements into commands that operates a wheelchair. This work used many spatial patterns of ERD on mu rhythms along the sensory-motor cortex and the resulting classification accuracy for online and offline tests was 79.48% and 85.00%, respectively. The authors of [19] proposed an EEG-based BCI system that controls hand prosthesis of paralyzed people by movement thoughts of left and right hands. They reported an accuracy of about 90%.

In [20], a hybrid BCI control strategy is presented. The authors expanded the control functions of a P300 potential based BCI for virtual devices and MI related sensorimotor rhythms to navigate in a virtual environment. Imagined left/right hand movements were translated into movement commands in a virtual apartment and an extremely high testing accuracy results were reached. Homri, et al. [21] applied the Daubechies, Coiflet and Symmlet wavelet families to a dataset of MI to extract features and describe right and left hand movement imagery. The authors reported that the use of Linear Discriminate Analysis (LDA) and Multilayer Perceptron (MLP) Neural Networks (NNs) provided good classification results and that LDA classifier achieved higher classification results of up to 88% for different Symmlet wavelets. Tolić and Jović [22] used the discrete wavelet transform (DWT) to create inputs for a NNs classifier and the authors reported a very high classification accuracy of 99.87% for the recognition of some mental tasks.

III. Data Preparations

A. *The EEG Dataset*

In this work, we used the EEG dataset that was created and contributed to PhysioNet [23] by the developers of the BCI2000 [24] instrumentation system. The dataset is publically available online at http://www.physionet.org/pn4/eegmmidb. It consists of more than 1500 one or two minutes-duration EEG records obtained from 109 healthy subjects. Subjects were asked to execute and imagine different tasks while 64 channels of EEG signals were recorded from the electrodes that were fitted along the scalp.

In the records of the dataset that are related to the current research, each subject performed three experimental runs of imagining moving fists. During each two-minute run, the left or right side of a computer screen shows a target. The subject imagines opening and closing the corresponding fist until the target disappears where he relaxes. This was repeated 15 times during each two-minute run. Then the obtained EEG signals were recorded according to the international 10-20 system as seen in Fig. 1. For this work, we created a subset of three two-minute runs for 20 subjects for a total of 900 events (45 imagined events per subject).

B. *Channel Selection and Filtering*

It was shown in the literature that most of the EEG channels are representing redundant information [6]. In addition, it was concluded that the neural activity that is mostly correlated to the fists movements is almost exclusively contained within the channels C_3, C_4, and C_Z of the EEG channels as depicted in Fig. 1 [25, 26]. So, we assumed that there is no need to analyze all the available EEG channels and it is more efficient to process the C_3, C_4, and C_Z channel.

EEGs are noisy and non-stationary signals that have to be filtered to get rid of the unnecessary content from the raw signals [27]. As shown in Fig. 2, the first step of the proposed system is to filter the selected channels for the purpose of removing the DC (direct current) shifts and minimizing the presence of filtering artifacts at epoch boundaries. This was accomplished by applying a band pass filter from 0.5Hz to 50Hz using the interactive MATLAB toolbox EEGLAB [28].

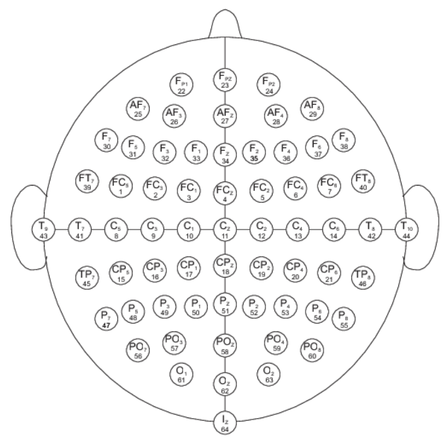

Figure 1. The International 10-20 system as seen from above the head.

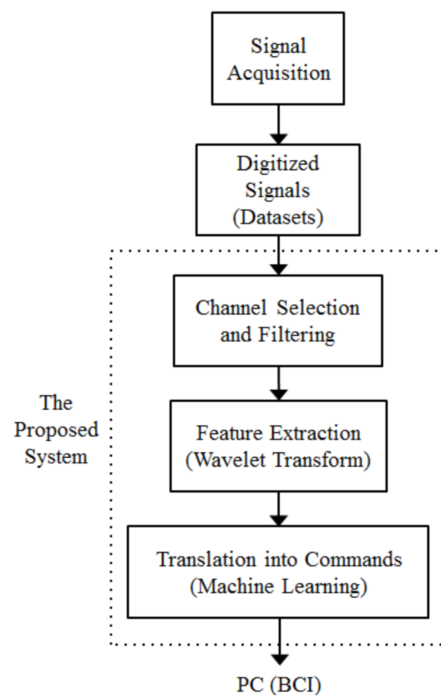

Figure 2. A block diagram of the proposed system.

EEG signals are usually masked by physiological artifacts that produce huge amounts of useless data [29]. Eye and muscle movements could be good examples of these artifacts that constitute a challenge in the field of BCI research. Automatic Artifact Removal (AAR) automatically removes artifacts from EEG data based on blind source separation and other various algorithms. The AAR toolbox [30] was implemented as an EEGLAB plug-in and was used to process our EEG data subset on two stages: Electrooculography (EOG) removal using the Blind Source Separation (BSS) algorithm then Electromyography (EMG) Removal using the same algorithm [31].

C. *Event extraction*

A subject imagines opening and closing his fist (right or left) and keeps doing this for 4.1 seconds then he takes a rest for the duration of 4.2 seconds. Each two-minute EEG record includes 15 events that are separated by a short neutral period where the subject relaxes. These events count up to a sum of 120.3 seconds representing the two-minute record. In this work, data that are time locked to a specific event type were split in a separate vector. As the Physionet EEG dataset was sampled at 160 samples per second, each vector includes 656 samples (values) of the original recorded EEG signal. And because we used the available records for 20 subjects, our dataset included 900 vectors representing imagined left or right fists movements.

IV. Discrete Wavelet Transform

A. *Wavelet Analysis for EEG signals*

The Wavelet transform analysis was used in a wide range of research topics within the field of signal processing. Based on a multi-resolutions process, the wavelet properties of a scalable window allow pinpointing signal components. These properties of dilation and translation enable the extraction of all components for every position by creating different scales and shifted functions (in time domain) of a signal [32, 33]. As a result, wavelet finer and large scaling, permit all information of the signal (the big picture), while small scales shows signal details by zooming into the signal components.

For discrete data, such as the datasets used in the current work, the Discrete Wavelet Transform (DWT) is better fit for analysis. It was shown in [34] that a suitable wavelet function must be used to optimize the analysis performance. A large selection of DWT mother wavelets, such as the Daubechies, Symmlet, and Coiflet, is available to be used in our work [21]. But the Daubechies (Db) family of wavelet functions was proved to be the most suitable wavelet in similar applications [34-37]. So, we decided to calculate the Daubechies orthogonal wavelets Db1-Db10 in this work.

As shown in Fig. 3, the main purpose of the DWT is to decompose the recorded EEG signal into multi-resolution subsets of coefficients: a detailed coefficient subset (cD_i) and an approximation coefficient subset (cA_i) at the level *i*.

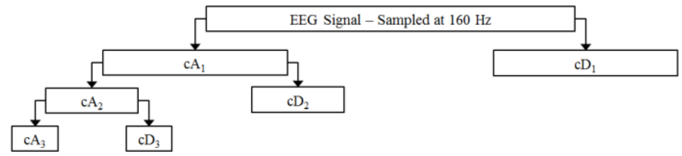

Figure 3. Multi-resolution decomposition of the EEG signal.

So, at the first decomposition level we obtain cD_1 and cA_1 then the first approximation cA_1 can be transformed into cD_2 and cA_2 at the second level, and so on. For our experiments, the decomposition level was set to generate three level details.

B. *Feature vectors construction*

The wavelet transformation of any EEG record at three levels results in four details and one approximation with the frequency ranges listed in Table I. There are many electrophysiological features that are associated with the brain's normal motor output channels [4, 38]. Some of these important features are the mu (8–12 Hz) and beta (13–30 Hz) rhythms [12]. We concluded from Table I that the details cD_2 and cD_3 provide proper representation for the mu and beta rhythms and we decided to extract the vectors of features from these details only. It was shown in [39] that the best amplitude estimators for neurological activities are the Root Mean Square (RMS) and the Mean Absolute Value (MAV) and it was proven that both of them were accurate inputs for recognition and classification systems. If we assume that the n^{th} sample of a wavelet decomposed detail at level *i* is $D_i(n)$, then the RMS and MAV at this level can be described, respectively, as:

$$RMS_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} D_i^2(n)} \tag{1}$$

$$MAV_i = \frac{1}{N}\sum_{n=1}^{N} \left|D_i(n)\right| \tag{2}$$

In our experiments, we applied the Daubechies orthogonal wavelets Db1 to Db10 for each one of the channels C3, C4, and Cz of an EEG record. This process was repeated for each event in our dataset of 900 vectors. Then, RMS and MAV were calculated using (1) and (2) for the details cD2 and cD3 of each instance.

TABLE I. FREQUENCY RANGE FOR THE DECOMPOSED DETAILS AND APPROXIMATION

Signal Component	Frequency Range
cD_1	40 – 80 Hz
cD_2	20 – 40 Hz
cD_3	10 – 20 Hz
cA_3	0 – 10 Hz

At the end of these calculations, 6 RMS features (3 channels × 2 details) and 6 MAV features were generated for each Daubechies wavelet. These features were numerically represented in a format that is suitable for use with SVMs NNs algorithms [40, 41] as described in the next section.

V. Classification Experiments

SVMs and NNs learning algorithms were used in [12, 13, 21, 22, 37] and provided good classification performance. A detailed description of SVMs and NNs can be found in [41]. The MATLAB NN toolbox was used for all the training and testing experiments. The training experiments were handled with the aid of the back-propagation learning algorithm [42]. SVM experiments were carried out using the "MySVM" software [43]. SVM can be performed with different kernels and most of them were reported to provide similar results for similar applications [6]. So, the Anova-Kernel SVM was used in this work.

NNs and SVMs classifiers were created with 12 inputs, representing both of the MAR and RMS features, and one output node representing the target functions left and right. In SVM, each of the degree and gamma parameters were varied from 1 to 10 and the number of hidden layers for the network was varied from 1 to 10. At each specific number of hidden layers (or a specific degree-gamma pair), 80% of the samples (720 events) were randomly selected and used for training and the remaining 20% (180 events) for testing. This process was repeated 10 times, and in each time the datasets were randomly mixed. For each number of hidden layers, the average accuracy was calculated for the ten training-testing pairs.

A huge number of training and testing experiments were carried out. Table II lists the best average accuracies with their associated classifier configurations. It can be noted that SVMs outperforms NNs in most experiments. We found that the use of a SVMs classifier of degree = 7 and gamma = 3 with inputs that were generated by a Db8 wavelet provided the optimum classification performance of an accuracy of 84.5%.

TABLE II. OPTIMUM CLASSIFICATION RESULTS ACHIEVED USING DIFFERENT DAUBECHIES FUNCTIONS WITH SVMS AND NNS.

Features	SVM			NN	
	Degree	*Gamma*	*Accuracy*	*Hidden Layers*	*Accuracy*
Db1	3	4	0.7100	7	0.7061
Db2	2	6	0.7860	2	0.7754
Db3	3	5	0.8022	5	0.7906
Db4	7	6	0.8013	5	0.7972
Db5	5	4	0.8175	9	0.8213
Db6	1	9	0.7940	6	0.7341
Db7	2	7	0.7901	6	0.7469
Db8	7	3	0.8449	9	0.8023
Db9	3	9	0.7366	7	0.7122
Db10	8	6	0.8034	6	0.7910

A NNs classifier of 9 hidden layers with inputs that were generated by a Db5 wavelet provided an accuracy of 82.1%. These are very promising result as it was obtained for imagined movements without any previous knowledge about the subject.

VI. Conclusions

This work presents a classification system that can analyse EEG signals and associate them with imagined left and right fist movements. Features were extracted using the Daubechies wavelets and some amplitude estimators. The performances of SVMs and NNs were compared as classifiers. Extensive experiments were carried out and promising results were obtained. The system was able to correctly classify EEG signals with up to 84.5% accuracy using SVMs. With this result, we believe that our system can provide more functionalities if used as a control interface for computer games, artificial limbs, or robots.

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