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Mind Controlled Universal TV Remote Control

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Abstract**:** *The main goal of this work is to combine our previous efforts in the analysis of Electroencephalography (EEG) signals and translate some mental commands into a universal TV remote control signals. The suggested system uses EEG signals as a communication path between brains (using a wireless EEG headset) and TVs (using remote controls). The Daubechies orthogonal wavelets were applied to analyze the signal records obtained from the PhysioNet EEG dataset then different amplitude estimators for the wavelet coefficients were selected to extract many features. The extracted features were normalized and used as inputs for Support Vector Machines (SVMs) and Neural Networks (NNs) to generate the needed decision rules. The proposed real time implementation of the system is presented and the testing results showed excellent performance. It is believed that this system could be helpful for disabled people as they can control their televisions via mental commands.*

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

1. Introduction

Electroencephalography (EEG) is defined by Niedermeyer and Silva in [1] as 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. In typical EEG tests, the brain's activity is monitored using electrodes that are fixed on the scalp [2]. Wearable EEG headsets capture 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 [3]. Such devices were known for their popular use in helping disabled individuals providing them a new channel of communication with the external environment and offering a feasible tool to control artificial limbs [4-8].

EEG signals were analysed in our previous research [9-12] to recognise signal patterns for executed and imagined, left and right movements for both fists and feet. The translation approach used to transform EEG signal patterns into machine commands reflects the strength of Brain-Computer Interface (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.

The authors of [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

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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.

In [17], 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. The Daubechies, Coiflet and Symmlet wavelet families were applied in [18] 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. The authors of [19] 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.

2. The Proposed Brain TV Interface

There are many wearable EEG headsets, such as the one designed by Emotive [20] or NeuroSky [21], that can be used to recognise mental commands. Emotive's EEG headset, shown in Fig. 1, provides high resolution data using 14 EEG channels and 2 references which can be translated into wide range of facial expressions, emotional states, and mental commands as listed in Table 1.

Fig. 1: Emotiv EPOC / EPOC+ wireless EEG headset

TABLE I: Possible detections provided by the Emotive EPOC+, EPOC, and INSIGHT headsets.

Facial expressions	**Emotional States**	**Mental commands**
Blink	Instantaneous excitement	Push
Left wink	Long term excitement	Pull
Right wink	Stress	Lift
Furrow (frown)	Engagement	Drop
Raise brow (surprise)	Relaxation	Left
Smile	Interest	Right
Clench teeth (grimace)	Focus	Rotate clockwise
Look left	Meditation	Rotate anticlockwise
Look right	Frustration	Rotate forwards
Laugh		Rotate backwards
Smirk (left side)		Rotate left
Smirk (right side)		Rotate right
		Disappear

It is shown in [9] that the recorded EEG data have to be passed through proper set of filters and then the content of interest has to be represented by features that are accepted by machine learning algorithms. The result of these steps is an array of decision rules that can be translated, as required, into commands as depicted in Fig. 2.

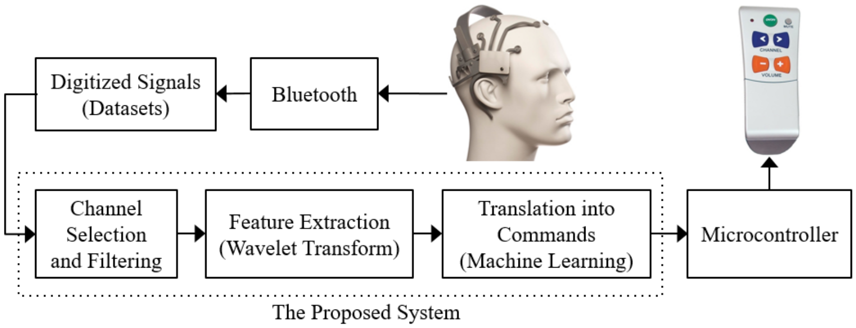

Fig. 2: A block diagram for the proposed brain TV interface

2.1. EEG Data

In this work, we used the EEG dataset that was created and contributed to PhysioNet [22] by the developers of the BCI2000 [23] 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. Each subject performed the following tasks: a one-minute baseline run with eyes open, a one-minute baseline run with eyes closed, three two-minutes experimental runs of imagining moving the right or left fists while the left or right side of a computer screen is showing a target, and three two-minutes experimental runs of imagining moving both fists or both feet while the top or bottom side of a computer screen is showing a target. Then the obtained EEG signals were recorded according to the international 10-20 system as seen in Fig. 3. For this work, we created a subset for 100 subjects including 8 runs per subject.

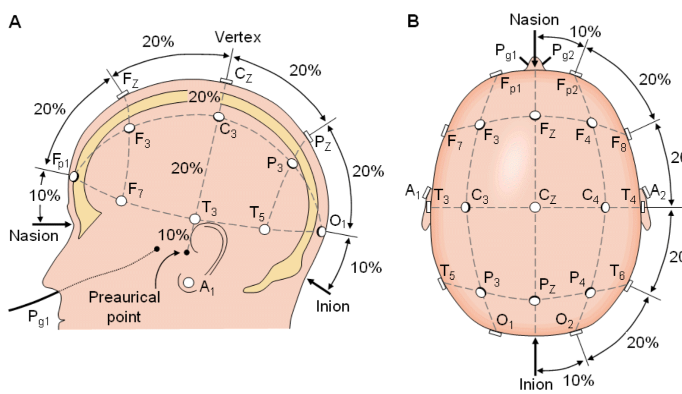

Fig. 3: The international 10-20 system [24] as seen from (A) left and (B) above the head. (Redrawn from [25])

2.2. Channel selection and filtering

It was concluded in [26, 27] that the neural activity that is mostly correlated to the fists movements is almost exclusively contained within the C3, C4, and Cz channels. In addition, it is reported in [2] that most EEG channels represent redundant information. Therefore, only channels C3, C4, and Cz were analysed in this research work. Data of these channels were filtered, using a band-pass filter (0.5-50 Hz), for the purpose of removing the DC shifts and minimizing the presence of filtering artifacts at epoch boundaries [28]. The Automatic Artifact Removal (AAR) toolbox [29] was used to remove the useless data, caused by physiological artifacts, from our EEG subset.

A subject imagines opening and closing a fist (or both fists/feet) and keeps doing this for 4.1 seconds then he takes a rest for the duration of 4.2 seconds. This means that each two-minute EEG run includes 15 events that are separated by a short neutral period where the subject relaxes. As the Physionet dataset was sampled at 160 samples per second, each vector includes 656 samples of the original recorded EEG signal. And because we used the available records for 100 subjects, our subset included 18000 vectors representing imagined left fist, right fist, both fists, and both feet movements. An additional 1500 vectors were extracted from the one-minute baseline run (with eyes open) and another 1500 vectors from the one-minute baseline run with eyes closed. So, the total number of extracted events was 12000 samples.

3. The Discrete Wavelet Transform (DWT)

The DWT 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 [30, 31]. It was shown in [32] 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 [18]. But the Coiflet (Coif) family of wavelet functions provided the best classification performance in our previous work [9, 11]. So, we decided to calculate the Coiflets wavelets Coif1-Coif5 in this work. It is clear from Fig. 4 how the DWT decomposes 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*. 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 four level details.

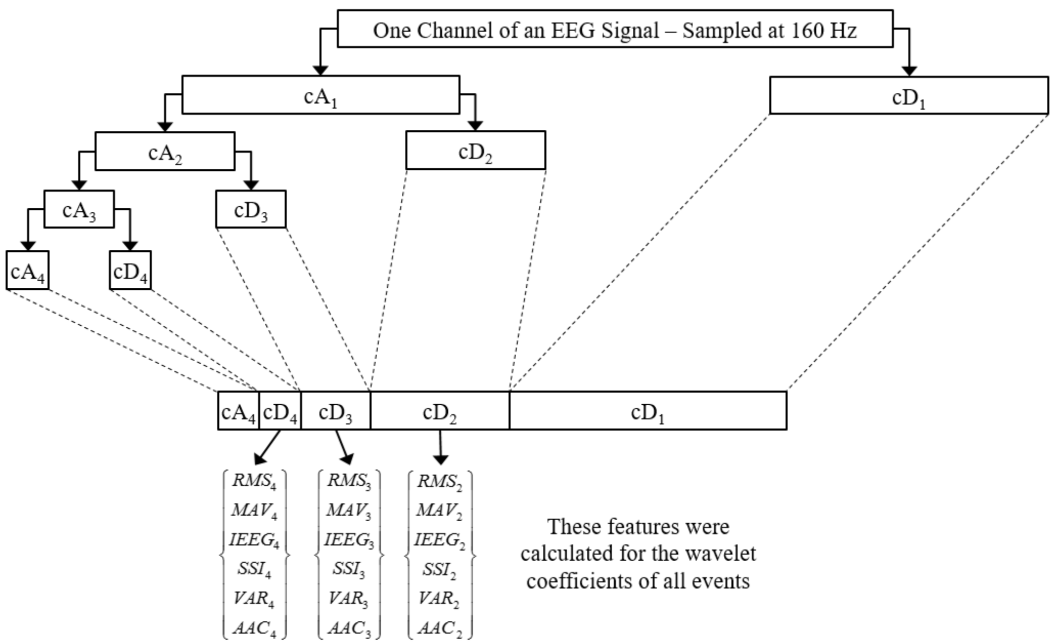

Fig. 4: The multi-resolution decomposition of a sample EEG signal.

All EEG signals in the subset were sampled at 160Hz. So, the wavelet transformation of each record at four levels results in four details and a single approximation as listed in Table 2.

TABLE II: 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
cD_4	5 – 10 Hz
cA_4	0 – 5 Hz

As explained in [11], the details cD_2, cD_3 and cD_4 provided proper representation for the activities of interest. So, we decided to extract the vectors of features from these details only. The Coiflets wavelets 1 to 5 were applied for each one of the selected channels. This process was repeated for each event in our dataset of 12000 vectors. Many amplitude estimators for neurological activities were defined mathematically in [9]: Root Mean Square (RMS), Mean Absolute Value (MAV), Integrated EEG (IEEG), Simple Square Integral (SSI), Variance of EEG (VAR), and the Average Amplitude Change (AAC). All of these estimators were calculated for the details cD_2, cD_3 and cD_4 of each instance. At the end of these calculations, 9 features of each estimator (3 channels, 3 details each) were generated for each Coiflets wavelet. These features were numerically represented in a format that is suitable for use with SVMs and NNs algorithms.

4. Machine Learning and Real Time Implementation

SVMs and NNs learning algorithms were used in [12, 13, 18, 19, 33] and provided excellent classification performances. SVM can be performed with different kernels and most of them were reported to provide similar results for similar applications [2]. As shown in Fig. 5, NNs and SVMs classifiers were created with 9 inputs, representing features of one estimator. The SVM classifier has one output node representing the target function: closed eyes/opened eyes. The NN classifier has one output node that has five possible classes: opened eyes, left fist, right fist, both fists, and both feet. Both classifiers were integrated such that the NN classifier is only enabled when the eyes are open.

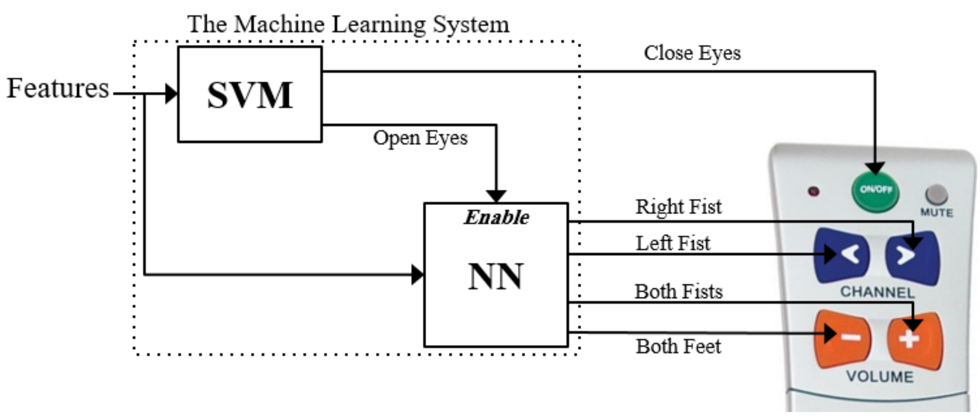

Fig. 5: The Hybrid Machine Learning Training/Testing System

The system of Fig. 5 assumes reading a test EEG record to be able to extract the features needed for the SVM and NN decision rules and provides near-real time actions. The default configurations of this system are to translate the "closing eyes for 2s" activity into the on/off remote button, the imagined left/right fists into changing the channel forward/backward, and both fists/feet movements into the increase/decrease volume buttons.

In SVM, each of the degree and gamma parameters were varied from 1 to 10 and the number of hidden layers for the neural network was varied from 1 to 20. At each specific number of hidden layers (or a specific degree-gamma pair), 80% of the samples (9600 events) were randomly selected and used for training and the remaining 20% for testing. This process was repeated 20 times, and in each time the datasets were randomly mixed. For each specific configuration, the average accuracy was calculated for the twenty training-testing pairs.

A huge number of training and testing experiments were carried out as described in [9]. It was found that the use of a SVMs classifier of gamma = 7 and degree = 5 with inputs that were generated by a Coif3 wavelet and MAV features provided the optimum classification performance of an accuracy of 72.04%. In addition, a NNs classifier of 13 hidden layers with inputs that were generated by a Coif2 wavelet and IEEG features provided an accuracy of 70.62%. These are very promising results as they were obtained while most of the available data are for imagined movements.

5. Conclusions

In this research work, an EEG controlled universal TV remote control system was presented. It suggests the use of the available commercial EEG headsets to translate mental commands into digital signals that can be transmitted by TV remote controls. This system can be easily used by disabled people as a channel of communication with TVs. EEG signals were analysed using the discrete wavelet transform and machine learning algorithms and promising classification performances were obtained.

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