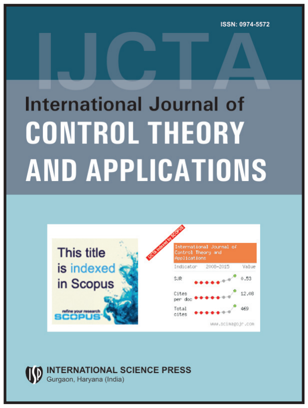

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EEG Based Machine Learning Approach to Handle Internet of Things

Akhil M.R.[a], Eldo P Elias[b] and Surekha Mariam Varghese[c]

[a-c]*Department of Computer Science and Engineering, M.A College of Engineering, Kothamangalam, Kerala, India. Email: [a]akhilmr1992@gmail.com; [b]eldope@gmail.com; [c]surekha.laju@gmail.com*

Abstract: For many years Brain-Computer Interfaces (BCI) research programs have been very popular. It uses brain waves or EEG (electroencephalogram) signal as input and performs computation based on this input to produce the output. The classification algorithm of the EEG signals has attracted much attention nowadays. The proposed system is aiming for a autonomous system that is capable of analysing and classifying EEG signals to handle different house hold equipments connected to the system. The EEG signal is collected by BCI equipment. After feature extraction and classification, man's thoughts are combined with the different dictates. The wavelet entropy is treated as one of the main feature of the input waveform. The system is capable of eliminating noise interference with the use of digital filters. Once it is completed the communication between brain and peripheral equipment can be established to perform specific tasks. Implementation of such a system could open a new communication world for patients with severe motor deficiencies like, for example, patients in a late stage of amyotrophic lateral sclerosis (ALS), who have lost control over every motor output and every communication with their surroundings.

Keywords: BCI, DWT, Support Vector Machine, Wavelet energy, IoT, PIC.

1. INTRODUCTION

The electroencephalogram (EEG) is a represents the electrical activity of the brain from the scalp. The first recordings were made by Hans Berger in 1929 although similar studies had been carried out in animals as early as 1870. The activities in the brain are influenced by the electrical activity from the brain structures underneath the cortex. Electroencephalogram is the recorded representation of these electrical activity produced by firing of neuron within the brain along the scalp.

EEG signal is mostly used in clinical assessments of the state of the brain and for assessing disorders of brain function. Electrical signals produced in the brain are monitored in a non-invasive manner by measuring the electrical potential variation on the scalp. Conventional method for EEG measurement is by strategically placing several small electrodes on the scalp, and forming a contact using conductive gel [2]. One electrode, usually at the base of the skull, acts as a reference point for the ground signal. Different channels of data are created by measuring the voltage differences between neighboring electrodes based on ground signal. For recording of EEG, electrodes will be pasted at some key points on the subject's head. Electrodes pick up the signals and pass it to recording device that is connected to electrodes. To overcome the complexity of conventional wet electrodes (using electrolytic gels) methods, dry electrode are now used in portable EEG measuring devices. Once the signal is recorded it can be used in prediction of a person's thoughts. This can be of great help for people with motor disabilities.

Organization of the paper is as follows Section I Introduction. Section II Related Studies, Section III Proposed Methodology, Section IV Conclusion.

2. RELATED WORK

The EEG signal consists of time varying potential differences on the scalp caused by the electrical activity of neurons in the brain. It is measured with electrodes placed on standard positions on the head. For many clinical and research applications, the name and location of these electrodes are specified by the international 10/20 system [2]. This system is based on the relationship between area of cerebral cortex and the location of electrodes. The '10' and '20' refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. The amplitude of a typical EEG signal ranges from 5 to 200 μV and frequency ranges from 1 to 100 Hz.

The visual analysis of the signal cannot be accurately. This method is very subjective and does not provide any standardization or statistical analysis. It is also time consuming. So many other methods are proposed in the analysis of EEG signal.

Spectral analysis of the EEG signal can be used in identifying the dominant frequencies in the signal. Different rhythms such as Alpha, Beta, Delta, Theta and Gama are grouped according to their frequency [3] as shown in Table 1.

Table 1
EEG Wave Frequency Components

Wave	*Frequency*	*Characteristics*
Gama	100-38 Hz	Strong focus
Beta	38-15 Hz	Active Thinking
Alpha	14-8 Hz	Relaxed Thoughts
Theta	7-4 Hz	Creative Thoughts
Delta	3-0.5 Hz	Deep Sleep

The temporal analysis of the EEG determines when these different rhythms appear and disappear, and keeps track the signal. Finally, the spatial analysis estimates the distribution of these rhythms over different regions of the brain. EEG signals are not deterministic and they have no special pattern like electrocardiogram (ECG) signals. Hence EEG signals are considered as non stationary signals. This gives us new challenges in the next phase feature extraction of the EEG signal.

A. Feature Extraction

There are no general methods for EEG signal analysis. So we normally rely on traditional signal analysis methods like time domain, frequency domain and wavelet based signal processing. These techniques use the frequency and time domain features in the classification models to determine the optimal feature set and combine with classifiers that gives the highest classification performance.

Since the early days of automatic analysis of EEG signals, representations based on correlation and Fourier transform have been applied [4]. The Fast Fourier Transformation (FFT) algorithm, invented in 1965 deserves much of the credit for early progress in this field as it significantly simplified computation of spectral coefficients [5]. However, these methods are less suited for the frequency decomposition of the EEG signal due to the non stationary property and presence of multi components in the EEG signal. Time-frequency methods were shown to outperform conventional methods of frequency analysis [6]. Indeed these methods have a long history of application to EEG [7]. The choice of time-frequency distribution is crucial for the efficiency of the proposed approach for analysis.

Li Wang et. al., [8] uses the feature extraction technique of common spatial patterns (CSP), and then these vectors were classified by support vector machine (SVM). CSP is a supervised technique effective method to solve spatial filters based on the modulation of ERD/ERS. As the result of simultaneous diagonalization of the two corresponding covariance matrices, EEG signals of two different categories are projected into low-dimensional subspace by CSP spatial filters. The method was reported with an accuracies between 73.65% and 95.76%.

Boqiang Liu et. al., [9] wavelet entropy is treated as one feature. When different thinking task is carried out, the active area of the pallium is different. Therefore the information entropy involved in EEG signal is different. So the information entropy is able to be regarded as a classify feature. At the same time, the brain signal is non-linear, very complicated and unsmooth. And the wavelet can analyse the signal in both frequency domain and time domain. So the information entropy combined with the wavelet is applied in our research as a classify feature. This feature is named wavelet entropy. It can be used to classify in different state of thinking task.

Another important feature extraction method, wavelet transform which differs from the traditional Fourier techniques by the way in which it localizes the information in the time-frequency plane; in particular, it is capable of trading one type of resolution for the other, which makes it especially suitable for the analysis of non stationary signals. A review of using wavelets for EEG analysis was given by Samar et. al., [10].

A data selection algorithm depending on phase congruency to determine interictal spikes from the background EEG was proposed by Logesparan & Rodriguez-Villegas in 2011. The phase congruency denoising was performed by dynamic estimation and compensation for muscle activity in EEG. The approach involved the modification of traditional phase congruency to include the dynamic estimate of muscle activity in the input scalp EEG signal. The authors report that the performance of the data selection algorithm was enhanced to 80% sensitivity for more than 50% data reduction.

B. Classification of EEG Signal

The objective of classification is to describe a boundary between the classes and to label them based on their measured features. The classifier can be as simple as fixing a Threshold for features or more sophisticated, such as machine learning algorithms. In a Multidimensional feature space, this boundary is converted into a separating hyper plane. The purpose is to find the hyper plane that has the maximum distance from all the classes. Several clustering and classification techniques have been developed.

Haibin Zhao et. al., [12] discuss the combinations of wavelet entropy (we) and band powers (bp) for feature extraction and Linear Discriminant Analysis (LDA). It uses mutual information (MI) for evaluation because it take into account the magnitude of the outputs. The MI is the average amount of information that an observation provides about a signal. It can be used as a measure for the quality of the feedback provided to the subject. The aim of LDA was to use hyperplane to separate the data representing the different classes. The separating hyperplane is obtained by seeking the projection that maximizes the distance between the two classes means and minimizes the interclass variance.

Hafeez et. al., [12] uses discrete wavelet transform is applied on EEG signals and the relative wavelet energy is calculated in terms of detailed coefficients and the approximation coefficients of the last decomposition level. The extracted relative wavelet energy features are passed to classifiers for the classification purpose. The performance of four different classifiers was evaluated with four performance measures, i.e., accuracy, sensitivity, specificity and precision values as shown in Table 2. The accuracy was achieved above 98 % by the support vector machine, multi-layer perceptron and the K-nearest neighbour classifiers. The findings of this study demonstrated that the proposed feature extraction approach has the potential to classify the EEG signals recorded during a complex cognitive task by achieving a high accuracy rate.

Table 2
Evaluation results of classifiers

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
SVM	98.75	100	97.50	97.60
MLP	98.21	100	96.40	96.60
K-NN	98.21	99.60	96.80	96.90
Naïve Bayes	83.57	75.00	92.10	90.50

3. PROPOSED WORK

A novel technique for the automated analysis of EEG signal is proposed which is capable of classifying the signal based on different cognitive task thoughts. The method is based on classification of EEG signal using a Multi class SVM which uses wavelet transform method for feature extraction.

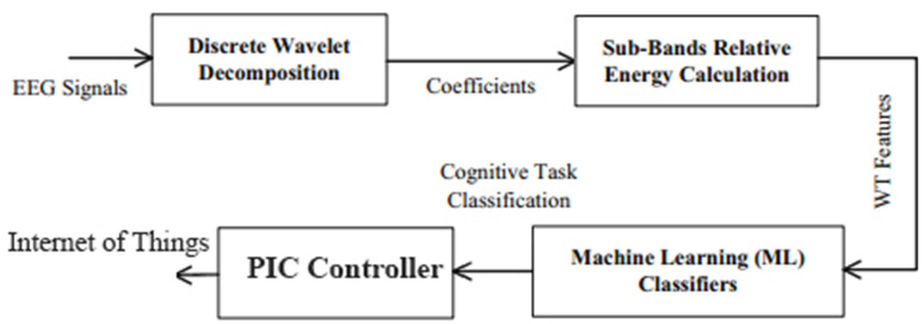

Figure 1: Basic Architecture of the system

A. Signal Acquisition

Signal acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Signal acquisition systems typically convert analog waveforms into digital values for processing. The components of Signal acquisition systems include:

- Sensors, to convert physical parameters to electrical signals
- Signal conditioning circuitry, to convert sensor signals into a form that can be converted to digital values.
- Analog-to-digital converters, to convert conditioned sensor signals to digital values.

Electrical signals produced in the brain can be monitored in a non-invasive manner by measuring variations in potential on the scalp. This EEG measurement is achieved by strategically placing several electrodes on the scalp, and forming a contact using conductive gel. One electrode, usually at the base of the skull, acts as a reference (ground) signal, and various channels of data are created by measuring the voltage differences between neighbouring electrodes. The name and location of these electrodes are specified by the international 10/20 system [2]. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The '10' and '20' refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. Figure 2 represents the international 10/20 system for signal acquisition.

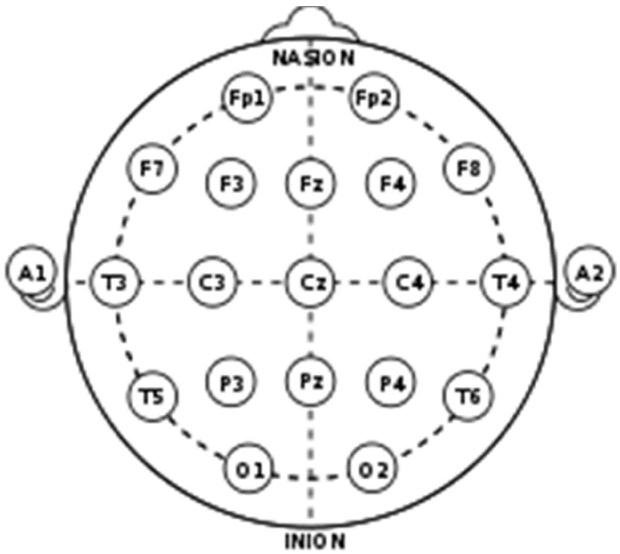

Figure 2: International 10/20 System

B. Preprocessing Signal

In biomedical signal processing, it is important to determine the noise and artifacts present in the raw signals so that their effect on feature extraction can be minimized. The preprocessing stage attempts to eliminate these artifacts without losing relevant information. The relevant information extraction from raw signals is a critical step in EEG pattern classification due to its direct influence on classification performance.

In our method, signals acquired by the raw EEG dataset are contaminated by noise and signals corresponding to cognitive task performed by the subject. Since we are interested only in the part of signal that relates to the normal tasks, we can eliminate the higher frequency components from this signal. Since the required frequency range is from 0 to 48Hz, we use a band pass filter to do the same. This filtering process can eliminate a large amount of noise signal which lies in the higher frequency range[12].

C. Feature Extraction

We are using the Wavelet Transform method for feature extraction of the EEG signal. Wavelet transform (WT) has been developed into an important tool in feature extraction and non - stationary signal analysis. WT employs long time windows for more precise low frequency information, and short time intervals for high frequency information.[12].

The output of the first high pass and low pass filters are referred to as the approximation and detailed coefficients, represented by A1 and D1, respectively. The A1 is further disintegrated and the procedure is repeated till the specified number of decomposition levels is reached (see Figure:4) [14,15].

The dilation function $\varphi j, k(n)$ is dependent on the low pass filter, and the wavelet function $\psi j, k(n)$ is follows the high pass filter, which is denoted as follows.

$$\varphi j, k(n) = 2j/2h(2jn - k)$$

$$\psi j, k(n) = 2j/2g(2jn - k)$$

where, $n = 0, 1, 2, \ldots, M - 1$; $j = 0, 1, 2, \ldots, J - 1$; $k = 0, 1, 2, \ldots, 2j - 1$; $J = \log 2(M)$; and M is the length of the signal [16]. The maximum level of decomposition is specified depending on the principal frequency components in the given signal [13]. The coefficients of the DWT are referred to as the dot product of the original time series and the designated basis functions. The approximation coefficients Ai and the detailed coefficients Di in the ith level are denoted as [13].

$$\mathbf{Ai} = \frac{1}{\sqrt{\mathbf{M}}}\sum_{n} x(n) \times \varphi j,k(n)$$

$$\mathbf{Di} = \frac{1}{\sqrt{\mathbf{M}}}\sum_{n} x(n) \times \psi\_j,k(n)$$

where, $k = 0, 1, 2, \ldots, 2j - 1$ and M is the length of the EEG time series in the discrete points.

The wavelet energy at each decomposition level $i = 1, 2, 3, \ldots, L$ is computed as follows:

$$\mathbf{EDi} = \sum_{j=1}^{\mathbf{N}} |\mathbf{Dij}|^2$$

$$\mathbf{EAi} = \sum_{j=1}^{\mathbf{N}} |\mathbf{Aij}|^2$$

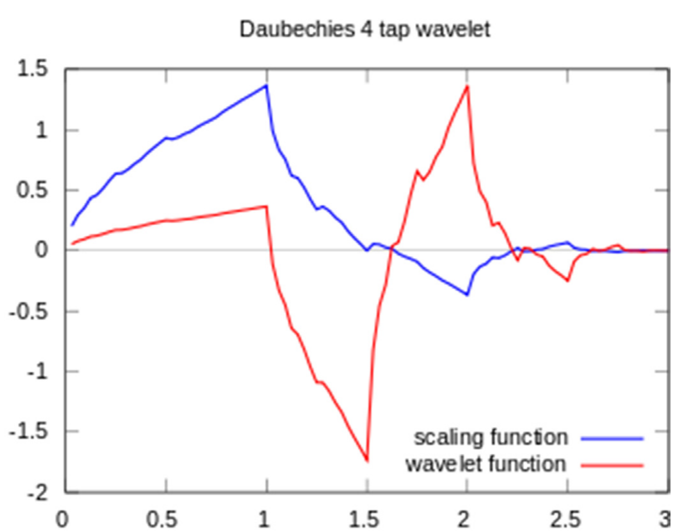

Figure 3: Daubechies wavelet

Feature extraction using wavelet transform enables signals to undergo wavelet decomposition with different scales. Wavelet decomposition generates different wavelet coefficients on each level, which are considered as features for the signal. Figure 4 denotes wavelet decomposition up to three scales. In the proposed method, the EEG signals undergo wavelet decomposition with to 4 levels using db4 wavelet.

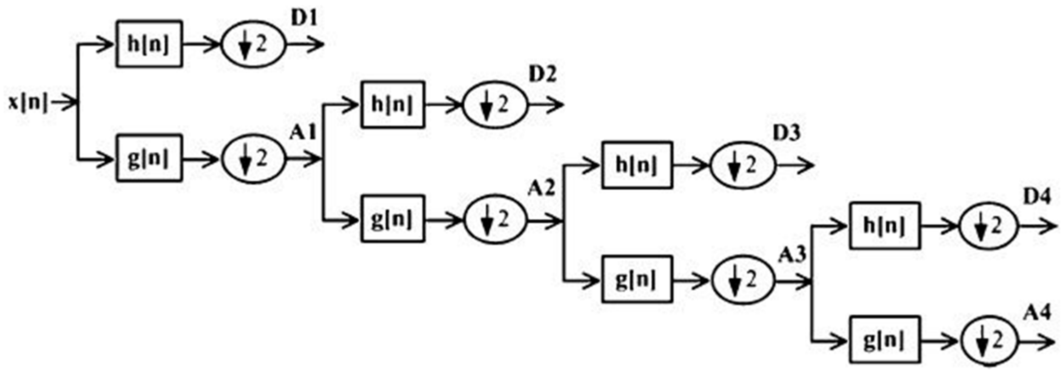

Figure 4: DWT Sub band decomposition

D. Classification

The objective of classification is to describe a boundary between the classes and to label them based on their measured features. The classifier can be as simple as fixing a threshold for features or more sophisticated, such as machine learning algorithms. In a multidimensional feature space, this boundary is converted into a separating hyper plane. The purpose is to find the hyper plane that has the maximum distance from all the classes. Several clustering and classification techniques have been developed. A classifier is a technique that utilizes various independent variable values (features) as input and predicts the corresponding class to which the independent variable belongs [17]. In the EEG signal analysis, the features can be any kind of extracted information from the signal, such as energy, entropy, power etc. and the class can be the type of task or the stimulus used during the recording. A classifier has a number of parameters that need to be learned from training data. The learned classifier is a model of the association between the features and the classes. For example, for a given feature x of a class y, the classifier is a function f that predicts the class $y = f(x)$. After the learning, the classifier is able to predict new instances that have not been used in the training data.

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. When data is not labeled, a supervised learning is not possible, and an unsupervised learning is required, that would find natural clustering of the data to groups, and map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering (SVC) and is highly used in industrial applications either when data is not labeled or when only some data is labeled as a preprocessing for a classification pass; the clustering method was published.

SVMs have been used to find the hyperplane for multidimensional data. The basic idea behind the SVM is to find a hyperplane in a feature space that optimally separates two classes. SVM yields a unique solution that can be shown to minimize the expected risk of misclassifying unseen examples. Training algorithms use the solution of a well known optimization problem constrained to quadratic programming that is computationally efficient and yields global solutions.

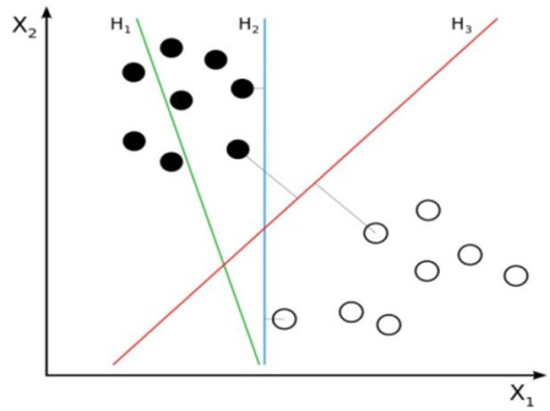

Figure 5: SVM Classifier

In our work since we need to classify the input data under multiple class label we need to have a multi class SVM. The formulation to solve multi-class SVM problems in one step has variables proportional to the number of classes. Therefore, for multi-class SVM methods, either several binary classifiers have to be constructed or a larger optimization problem is needed. Hence in general it is computationally more expensive to solve a multiclass problem than a binary problem with the same number of data. [18]

E. Output Signal Generation

Once the classification of the signal is completed we need to produce appropriate signals that need to be transferred to an embedded circuit. The construction of the electronic circuit will be done using PIC which will be programmed to operate individual house hold equipments based on the generated signals.

F. PIC Microcontroller

PIC is a family of microcontrollers made by Microchip Technology, derived from the PIC1650 originally developed by General Instrument's Microelectronics Division. The name PIC initially referred to Peripheral Interface Controller. The hardware capabilities of PIC devices range from 6-pin SMD, 8-pin DIP chips up to 100-pin SMD chips, with discrete I/O pins, ADC and DAC modules, and communications ports such as UART, I2C, CAN, and even USB. Low-power and high-speed variations exist for many types.

The manufacturer supplies computer software for development known as MPLAB, assemblers and C/C++ compilers, and programmer/debugger hardware under the MPLAB and PICKit series. Third party and some open-source tools are also available. Some parts have in-circuit programming capability; low-cost development programmers are available as well has high-production programmers.

In our work we are using pic microcontroller PIC6f877a which is able to control multiple devices connected to the circuit upon corresponding signal generated.

4. CONCLUSION

Through this work we introduce a machine learning approach for the classification of EEG signal based on the mental thoughts and there by controlling house hold equipments. This work uses discrete wavelet transform method for the feature extraction of the signal. For the classification part we are using Multi Class Support Vector Machine. After the classification of the signals based on different mental thoughts we generate signals to control an electronic circuit using which house hold equipments can be controlled. This work extends its reach to Internet of things via this electronic circuit. The implementation of such a system can be of great help for physically disabled people as well as people with motor disabilities. The application of this system can also be extended to the field of virtual reality implementation.

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