

# Towards Detection of Brain Tumor in Electroencephalogram Signals Using Support Vector Machines

M. Murugesan and Dr.(Mrs.).R. Sukanesh

**Abstract**—Brain tumor is an abnormal growth of cells within the brain or inside the skull, which can be cancerous or non-cancerous. Early detection and classification of brain tumors is very important in clinical practice. Electroencephalogram signal is one of the oldest measures of brain activity that has been used vastly for clinical diagnoses and biomedical researches. In this paper, we present an effective system for classification of electroencephalogram (EEG) signals that contain credible cases of brain tumor. The classification technique support vector machine is utilized in the proposed system for detecting brain tumors. In general, the EEG signals carry information about abnormalities or responses to certain stimulus in the human brain. However, EEG signals are highly contaminated with various artifacts, both from the subject and from equipment interferences. Initially, the artifacts present in the EEG signal are removed using adaptive filtering. Then the spectral analysis method is applied for extracting generic features embedded in an EEG signal. Precisely, Fast Fourier Transform for spectral analysis is used to separate the signal features which are buried in a wide band of noise. The radial basis function-support vector machine is trained using the clean EEG data obtained. With proper testing and training, we effectively classify the EEG signals with brain tumor. The key advent of the proposed approach is that it enables early detection of brain tumors initiating quicker clinical responses.

**Index Terms**—Adaptive filtering, Artifacts, Brain, Brain tumor, Electroencephalogram (EEG), Electro-oculogram (EOG), Fast Fourier Transform (FFT), Seizure, Spectral analysis, Support vector machine.

## I. INTRODUCTION

Neuromuscular disorders have affected around two million people in the United States [1]. An approximation of the overall occurrence is that 1 in 3500 of the world's population is anticipated to suffer from a disabling inherited neuromuscular disorder from childhood or in later life [2]. In a majority of cases, individuals affected may have no control over muscles that would generally be utilized for communication. Brain-Computer Interface (BCI) technology is an emerging technology which has the potential to contribute to the enhancement of living standards for those people by providing an alternative communication channel that does not rely on the peripheral nerves or muscles [3].

M. Murugesan, Assistant Professor, Dept of EEE, Syed Ammal Engineering College, Ramanathapuram, Anna University, Trichy, India. Ph: +91 9976937713, Email: [mmurugesanphd@gmail.com](mailto:mmurugesanphd@gmail.com).

Dr.(Mrs.).R. Sukanesh, Professor, Department of ECE, Thiagarajar College of Engineering, Madurai, India. Ph: +91 9442149445, Email: [drsukanesh2003@yahoo.com](mailto:drsukanesh2003@yahoo.com).

A BCI reinstates the exercising of nerves and muscles and the movements they produce with electrophysiological signals in combination with the hardware and software that interpret those signals into actions [1].

A BCI also encompasses the extraction of information from the highly complex electroencephalogram (EEG) [4].

Researching the properties of spatial-temporal organization of brain electrical activity (electroencephalogram or EEG) in a variety of functional conditions is one of the principal methods of studying brain activity. The study of EEG reorganization in organic brain damage with varying degrees of cerebral functioning disturbance is of vital significance. For a considerable number of years now, the utilization of EEG in neurosurgery has been focused on the revelation of brain lesions. Of late, due to the rapid advancement of neuro-radiology (computer tomography, magnetic resonance tomography), the utilization of EEG as a tool of topical diagnosis has become less relevant. The clarification of the extent of damage to integral brain activity and the level of de-compensation appears to be of superior relevance [5].

The EEG signal denotes the superposition of brain activities recorded as variations in electrical potentials at multiple locations over the scalp. The electrooculogram (EOG) signal is the chief and most widespread artifact in EEG analysis produced by eye movements and/or blinks [6]. Repressing eye-blink over a continued recording course is predominantly hard owing to its amplitude that is of the order of ten times larger than average cortical signals. Given the magnitude of the blinking artifacts and the high resistance of the skull and scalp tissues, EOG might contaminate the greater part of the electrode signals including those recorded over occipital areas. Lately, it has become extremely pleasing to efficiently eliminate the eye-blink artifacts without distorting the underlying brain activity [7].

The EEG signals absorb a great deal of information about the function of the brain. EEG acquired from scalp electrodes, is a superposition of a huge amount of electrical potentials arising from a number of sources (including brain cells i.e. neurons and artifacts) [8]. Nevertheless, the potentials arising from independent neurons inside the brain, not their superposition, are of major significance to the physicians and researchers to illustrate the cerebral activity. Direct measurements from the diverse centers in the brain necessitate placement electrodes inside the head, which in turn needs surgery. This was not suitable since it would cause pain and risk for the subject. An improved solution

would be to determine the signals of interest from the EEG obtained on the scalp [9]. Signal processing is utilized to handle diverse issues in EEG analysis including data compression, detection and classification, noise reduction, signal separation, and feature extraction. The study of these signals is significant both for research and for medical diagnosis and treatment. Fig. 1: illustrates a four second sample of an EEG data.

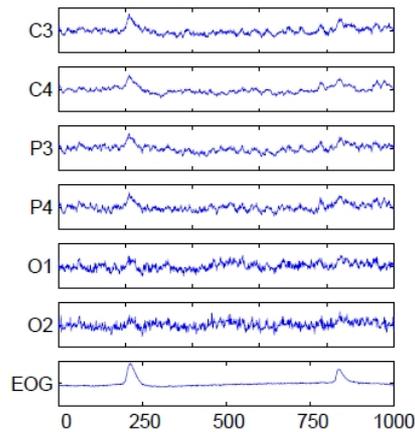


Fig. 1: A four second sample of an EEG data

Electroencephalogram (EEG), a representative signal encompassing information of the electrical activity produced by the cerebral cortex nerve cells, has been the widely employed signal for the clinical assessment of brain activities, and the identification of epileptiform discharges in the EEG [10]. The pattern of electrical activity is principally beneficial as well employed to investigate other conditions that might affect brain function, like head injuries, brain tumors or bleeding on the brain (hemorrhage). In our research we propose an efficient approach to explore the early detection of brain tumors with the aid of EEG Analysis.

#### A. Brain Tumor

A brain tumor can be defined as an abnormal growth of cells inside the brain or the skull, which can either be cancerous or non-cancerous (benign). Tumors that commence in brain tissue are referred to as primary tumors of the brain. Primary brain tumors are named according to the type of cells or the part of the brain in which they commence from [11]. They are described as any intracranial tumor produced by abnormal and uncontrolled cell division, usually either in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells), lymphatic tissue, blood vessels), in the cranial nerves (myelin-producing Schwann cells), in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers principally located in other organs (metastatic tumors) [12].

There are more than one ways of identifying brain tumors. A few of the patients with larger tumors complain of continual headache particularly while lying flat or coughing whereas others suffer symptoms from dysfunction in the brain area where the tumor has attacked or displaced normal tissue. Common symptoms comprise of weakness or numbness on one side of the body, language disturbance, or vision deficits. Brain tumors can as well be first identified

with a seizure. Seizures are the widespread initial presenting symptom for low grade tumors including astrocytomas (most regular kind of intrinsic brain tumor) and for tumors situated in brain regions where dysfunction does not constantly result in apparent clinical manifestations (frontal and temporal lobe of the non-language hemisphere, tiny tumors of the language dominant anterior frontal region) [13].

Around 50% of patients suffering from tumors are as well affected by seizures. Partial seizures are considered to be of the highest incidence, followed by seizures due to secondary generalization. The kind of seizure might differ with diverse histological subtypes, tumor location and extent. The fundamental patho-physiologic mechanisms of tumor-associated seizures are defectively comprehended and might comprise of alteration of peritumoral amino acids, regional metabolism, pH, neuronal or glial enzymes and protein expression, in addition to immunologic activity. The participation of altered distribution and function of N-methyl-d-aspartate (NMDA) subclasses of glutamate receptors has been recommended as well. On the whole, slow-growing benign tumors result in additional seizure problem than malignant tumors for the reason that rapidly growing malignant tumors attempt to destroy neurons in close proximity instead of stimulating them [14].

Seizure control is particularly significant in patients with brain tumors. Apart from the risks and negative effects that seizures produce in everyone, seizures may infrequently cause prolonged neurologic deficits due to the increased metabolic demand on already compromised brain tissue adjacent to a tumor. Physicians who treat brain tumor associated with seizures also need to be aware of other peculiar issues. Many patients obtain chemotherapy agents which may result in drowsiness, reduce white and red blood cell counts besides interacting with antiepileptic medications. Consequently, treatment needs to be tailored to the patient's anti-tumor therapy. For example, medications like phenytoin might boost the breakdown of certain chemotherapy agents (or steroids), thus sinking the amount of chemotherapeutic agent present to treat the tumor [19].

Premature detection and classification of brain tumors is very significant in clinical practice. Numerous researchers have projected diverse techniques for the categorization of brain tumors on basis of different sources of information [15, 16, and 17]. Regardless of the techniques introduced thus far for the extraction of information, analysis and visualization of EEG, brain tumor diagnosis frequently engages experienced physicians and is a nontrivial, time-consuming task chiefly owing to the following reasons [18]:

- Low evidence of symptoms: EEG is a propagation of internal electrical activity onto the scalp at a macroscopic level and might lose precise information and localization of a tumor besides becoming the result of global connected brain activity whose features differ from case to case.
- Variations in functionality and anatomy of brain tissues justify the reason behind variability of symptoms among subjects.

- Varying recording conditions, the presence of external stimuli and complexity of brain activity lead to non stationary EEG recordings over different sessions.

### B. Objective of Our Research

In our paper, we present an efficient classification system to detect EEG signals that possess probable cases of brain tumor. The classification technique employed is based on the theory of support vector machines (SVMs). Here, we describe SVMs that use different similarity metrics, including a simple dot product of signal vectors, polynomial versions of the dot product, and a radial basis function. The radial basis function SVM appears to provide superior performance in classifying functional classes of EEG signal when compared to the other SVM similarity metrics. EEG records carry information about abnormalities or responses to certain stimuli in the human brain. However, EEG signals are highly contaminated with various artifacts. Artifacts in EEG records are caused by various factors, like line interference, EOG and ECG (electrocardiogram). These noise sources increase the difficulty in analyzing the EEG and thus obtaining effective clinical information. For this reason, it is necessary to devise a method that decreases such artifacts in EEG records. First, to eliminate the artifacts present in the EEG signal, the method we employed is based on adaptive filtering. This method uses EOG signal as the reference input and subtracts EOG artifacts from recorded EEG signals. Then, we tackle the problems of generic features embedded in an EEG signal with the aid of spectral analysis method. Specifically, we use FFT for spectral analysis to separate the EEG signal features buried in a wide band of noise. With these set of features and the clean data, we principally use SVMs supervised classification based on RBF kernel to achieve effective classification. With the aid of organized training and testing of RBF using the EEG signal, we effectively classify the EEG signal with brain tumor. Early detection of brain tumors using the EEG signals is the primary benefit of this classification scheme.

The paper is organized as follows: section 2 briefs a comprehensive review of previous researches. The concepts utilized in brain tumor detection are detailed in section 3. In section 4, classification of brain tumors from EEG signal using support vector machine is detailed. Section 5 details the discussion of experimental analysis. Section 6 sums up with conclusion.

## II. PREVIOUS REVIEW

Our work has been inspired by a number of previous works available in the literature for artifacts removal and brain tumor detection using EEG signal. Some of them are described as follows:

A number of regression-based techniques have been devised to eliminate ocular artifacts (OAR) from EEG Signals. These regression based techniques encompasses of simple time-domain regression [20], multiple lag time-domain [9] and regression in the frequency domain [21]. Generally, the EEG and EOG are uncorrelated in regression methods, but in practice it is not the case. All these

regression-based methods necessitate calibration trials to be conducted initially to establish the transfer functions between each EOG and EEG channel.

One of the most recently proposed method, Independent Component Analysis (ICA) works on the assumption that the potential available in the scalp is a weighted sum of source; hence EOG and EEG signals can be separated individually by identifying their independent sources in the brain [22]. Anyhow, this method does not suit for online application and it necessitates data storage and off-line processing. Haas et al [23] recommended a general subtraction method, ARMAX, which assumes that the measured EEG is expressed as a linear combination of a background EEG and corrupting ocular artifacts. They also showed that the background EEG can be estimated by ARMAX method.

Scalp EEG has been employed as a clinical tool for the analysis and healing of brain disease. Habl et al. [24] studied a probabilistic ICA algorithm adapted by a kernel-based source density in order to segregate EEG signals from tumor patients into spatially independent source signals. In addition they have provided a statistical method to automatically recognize artifactual and tumor related ICA components.

During the diagnostics of brain tumor, EEG is chiefly relevant in evaluating how lesion affects the fundamental functionality is affected and how the brain acts in response to treatments (e.g. post-operative). Fadi N. Karamah and Munther A. Dahleh [18] pay attention on developing an automated system to recognize space occupying lesions in the brain with the aid of EEG signals. They have deal with major complications in relation with EEG to diverse tumor classes and propose an approach of feature extraction with the aid of wavelet techniques and classification through self organizing maps. By means of an incremental improvement in the characteristics and categorization techniques, results progress on a consistent basis in spite of the vagueness and variability of tumor features. At this juncture, they have illustrated that a different decomposition of the time-frequency plane offers an improved chance to extract clues regarding the aforementioned tumor classes than with traditional frequency bands.

Rosaria Silipo et al. [15] studied the tedious issue in the detection of brain tumor on basis of rest EEG analysis, depending upon the hypothesis that the EEG signal consists of additional hidden useful information than what is clinically employed.

The hidden dynamic of the pair (F3, F4) is evaluated against a hierarchy of null hypotheses, equivalent to one and two dimensional nonlinear markov models of growing order. Rest EEG records of 6 patients with proof of meningioma or malignant glioma in lead f4 or without any pathology were examined.

A study on the effects of the EMFs emitted by cellular phones on the human EEG in adults and children was carried out by Alexander V. Kramarenko and Uner Tan [25]. The EEG was found to display normal activity during exposure, apart from a minor raise in the global median frequency. Nevertheless, a short-lasting slow-wave activity transpired after a latent period of 15–20 s once the phone

was turned on. These slow-waves, within the delta range were examined periodically for every 15–20 s. Once the phone was turned off, they gradually declined in amplitude and disappeared in ten of min. They arrived at a conclusion that the EMFs produced by cell phones might be harmful for the human brain owing to the fact that the delta waves are pathological if observed in subjects who are awake. Conversely, the slow wave activity was found to be more marked in children than adults, demonstrating that the children might be more exposed to the health adversities resulting from mobile phones than adults, in all probability due to the fact that absorption of microwaves is maximum in an object about the size of a child's head; it is possible for the radiation to penetrate the thinner skull of an infant without any difficulty.

### III. CONCEPTS UTILIZED IN BRAIN TUMOR DETECTION

The concepts utilized in brain tumor detection such as artifacts, electro-oculogram, spectral analysis and support vector machine are detailed in the below subsection

#### A. Artifacts

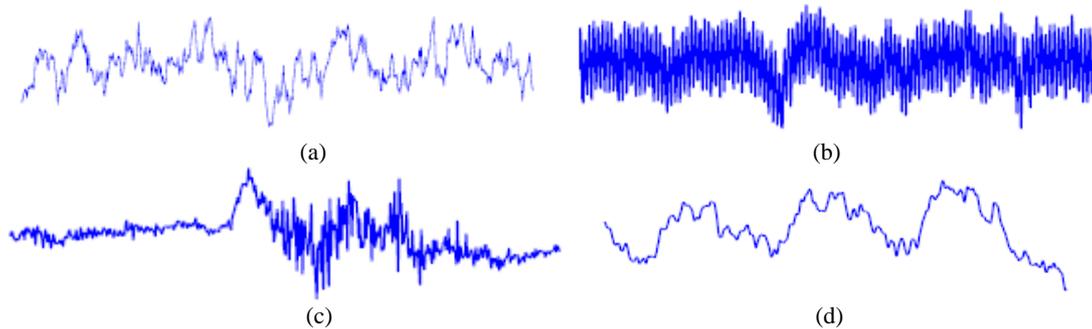


Fig. 2: Artifact Waveforms (a) Clean EEG (b) Line Noise (c) Muscle Activity (d) Pulse

**Line Noise:** Strong signals from A/C power supplies (see Fig. 2(b)) might possibly corrupt EEG data as it is shifted from the scalp electrodes to the recording device. Frequently this artifact is filtered by notch filters, except for lower frequency line noise and harmonics where it is considered undesirable. When the line noise or harmonics take place in frequency bands of interest they interfere with EEG that occurs in the same band [22]. Notch filtering at these frequencies might eliminate useful information. Line noise might corrupt the data from a few or all of the electrodes in accordance with the source of the problem.

**Muscle Activity:** Muscle activity (see Fig. 2(c)) might result out of activity in various muscle groups counting neck and facial muscles. These signals come with a wide frequency range and can be distributed over diverse sets of electrodes on basis of the location of the source muscles.

**Pulse:** The pulse, or heart beat, artifact (see Fig. 2(d)) appears once an electrode is positioned on or adjacent to a blood vessel. The expansion and contraction of the vessel induces varying voltages into the recordings. The artifact signal has a frequency of around 1.2Hz, but can differ with the state of the patient. This artifact either seems as spike or like smooth wave [23].

The surface electroencephalogram (EEG) describes the electrical activity of the brain got by scalp electrodes. The high quality EEG signals are greatly affected Artifacts. Their presence is thus critical for the precise assessment of EEG signal [26]. The recording process is liable to contaminate the EEG data at many points. Various factors, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram) can serve as causatives for artifacts in EEG. These noise sources augment the complexity in analyzing the EEG for obtaining clinical information. The artifacts can be divided into two major categories: technical and physiological artifacts. The most commonly observed physiological artifacts are owing to ocular, heart or muscular activity; of them the EOG artifacts are the most difficult [26]. Most of the artifacts mentioned here are biologically generated by external sources. Enhancing technology can reduce externally generated artifacts, such as line noise, but biological artifact signals must be eliminated only after the recoding process. Fig. 2 portrays waveforms of some of the most common EEG artifacts, each of which is discussed below.

#### Electro-Oculogram (EOG)

The electrical field around the eyes varies and generates an electrical signal, known as EOG, every time they move. While this signal spreads over the scalp, it becomes visible on the recorded EEG as noise or artifacts that need to be eliminated so as to stop its interpretation with background EEG [27]. Owing to the fact that the magnitude of the EOG artifact is frequently about the order of the amplitude of EEG signal; eliminating this artifact is one of the most significant issues in studying the brain activities. EOG artifacts are handled with the aid of a number of methods. Commonly, the subjects are requested to stop blinking or moving their eyes when the EEGs are recorded. Despite that this method might bring down the quantity of EOG artifacts. It possibly will produce other EEG signals since the subject keeps actively thinking about not moving the eyes. A different method of eliminating EOG artifacts is to eliminate segments that comprise of artifacts. Still, the subjects usually blink their eyes at some stage in the mental task [28]. Fig. 3 shows waveforms of the most common EEG artifacts Electro-oculogram.



Fig. 3: Electro-Oculogram Waveforms (a) Eye Blink (a) Eye Movement

**Eye Blink:** The eye blink artifact is a frequent phenomenon in EEG data. It generates a high amplitude signal that will possibly be many times larger than the EEG signals of interest (see Fig. 3(a)). Owing to its high amplitude it is possible for an eye blink to corrupt data on all electrodes including the ones at the back of the head (See Fig. 1). Eye artifacts are commonly measured more directly in the EOG, pairs of electrodes placed above and around the eyes. Regrettably, these measurements are contaminated with EEG signals of interest and thus simple subtraction cannot be looked upon as a removal option even when an accurate model of EOG diffusion across the scalp is available [22].

**Eye Movement:** Eye movement artifacts (see Fig. 3(b)) result out of the reorientation of the retinocorneal dipole [24, 20]. The diffusion of this artifact over the scalp is powerful than that of the eye blink artifact. Eye blinks and movements frequently occur at close intervals creating an effect as shown in Fig. 4.

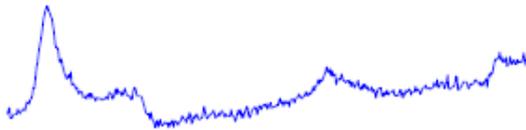


Fig. 4: Overlap of eye blink and eye movement artifacts.

### B. Spectral Analysis

Spectrum analysis deals with the exploration of cyclical patterns of data. The intention of the analysis is to decompose a composite time series comprising of cyclical components into a small number of underlying sinusoidal (sine and cosine) functions of specific wavelengths. Spectrum analysis is the practice of computing the frequency domain representation of a time domain signal and often utilizes the Fourier transform [29]. The Discrete Fourier Transform (DFT) is employed to compute the frequency content of analog signals that come across during circuit simulation the one that handles sequences of time values. The Fast Fourier Transform (FFT) is a competent method for the determination of DFT, and Star-Hspice employs it to offer a highly precise spectrum analysis tool. Spectral analysis in statistics is the process that decomposes a time series into a spectrum of cycles of varying lengths. Spectral analysis is referred to as frequency domain analysis as well [30].

The objective of spectral estimation is to provide a description of how power contained in a signal distributed (over frequency), based on a finite set of data. Power spectra Estimation is essential in a variety of applications, including

the detection of signals buried in wide-band noise [31]. The power spectral density (PSD) of a stationary random process  $x_n$  is mathematically related to the correlation sequence by the discrete-time Fourier transform. In terms of normalized frequency, this is given by

$$P_{xx}(\omega) = \frac{1}{2p} \sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-j\omega m} \quad (1)$$

This can be written as a function of physical frequency  $f$  (e.g., in hertz) by using the relation,  $\omega = 2\pi f / f_s$  where  $f_s$  is the sampling frequency.

$$P_{xx}(f) = \frac{1}{f_s} \sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-2\pi j f m / f_s} \quad (2)$$

The correlation sequence can be derived from the PSD by use of the inverse discrete-time Fourier transform:

$$R_{xx}(m) = \int_{-p}^p (P_{xx}(\omega) e^{j\omega m}) d\omega = \int_{-f_x/2}^{f_x/2} (P_{xx}(f) e^{2\pi j f m / f_s}) df \quad (3)$$

The average power of the sequence  $x_n$  over the entire Nyquist interval is represented by

$$R_{xx}(0) = \int_{-p}^p P_{xx}(\omega) d\omega = \int_{-f_x/2}^{f_x/2} P_{xx}(f) df \quad (4)$$

The average power of a signal over a particular frequency band  $[w_1, w_2]$   $0 \leq w_1 < w_2 \leq p$ , can be found by integrating the PSD over that band:

$$\overline{P}_{[w_1, w_2]} = \int_{w_1}^{w_2} P_{xx}(\omega) d\omega + \int_{-w_2}^{-w_1} P_{xx}(\omega) d\omega \quad (5)$$

### C. Support Vector Machine Classifier

A Support Vector Machine (SVM) achieves classification by an N-dimensional hyperplane construction which optimally classifies the data into two categories. SVM models are strictly associated to neural networks. To be more precise, a SVM model with a sigmoid kernel function is equal to a two-layer, perceptron neural network. In fact, Support Vector Machine (SVM) models and classical multilayer perceptron neural networks are close cousins. In using a kernel function, SVM's are an alternative training method for polynomial, whereas in radial basis function and multi-layer perceptron classifiers the weights of the network are computed by finding a solution to a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training [32].

In the parlance of SVM literature, a predictor variable is defined as an attribute, and a transformed attribute that is used hyperplane definition is termed as a feature. Feature selection is defined as the task of selecting the most appropriate representation [33]. A set of features describing one case (i.e., a row of predictor values) is called a vector. So the purpose of SVM modeling is to locate the optimal hyperplane that effectively breaks up clusters of vector in such a manner that one category cases of the target variable are on one side of the plane and other category cases are on the other size of the plane. The vectors adjacent to the hyperplane are the support vectors [34].

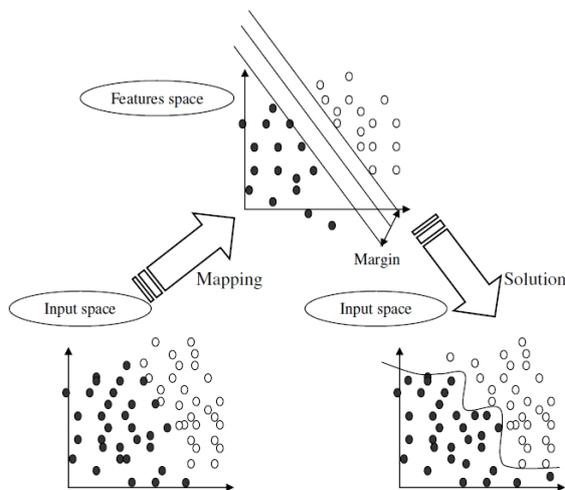


Fig. 5: SVM classification

SVM's are a useful classification method. Given instances  $x_i, i = 1, \dots, l$  with labels  $y_i \in \{1, -1\}$ , the main task in training SVMs is to solve the following quadratic optimization problem [35]:

$$\begin{aligned} \min_a f(a) &= \frac{1}{2} a^T Q a - e^T a \\ \text{subject to } 0 &\leq a_i \leq C, i = 1, \dots, l, \\ y^T a &= 0, \end{aligned} \quad (6)$$

where  $e$  is the vector of all ones,  $C$  is the upper bound of all variables,  $Q$  is an  $l$  by  $l$  symmetric matrix with

$Q_{ij} = y_i y_j K(x_i, x_j)$ , and  $K(x_i, x_j)$  is the kernel function.

**Exponential Radial Basis Function:** A radial basis function of the form, produces a piecewise linear solution which can be attractive when discontinuities are acceptable [36].

$$K(x, y) = \exp\left(-\frac{|x - y|}{2\sigma^2}\right) \quad (7)$$

#### IV. CLASSIFICATION OF BRAIN TUMORS FROM EEG SIGNAL

An evaluation over the literature surveyed states that there has not been many effective classification schemes for classifying cases of brain tumors from EEG possibly due to the aforesaid difficulties, chiefly symptom variability among different subjects and exhibition of diverse brain electric behavior under different lesions, the symptoms being most reliable under gliomas and less evident under brain stem tumors. In our proposed approach, we have devised an efficient EEG signal classification system for brain tumor detection employing the concepts of spectral analysis and SVM's. Initially the EEG Signals are subjected to the process of artifacts removal, which involves adaptive filtering and spectral estimation using Fast Fourier Transform (FFT). To get the filtered output, the data are convolved with the filter coefficients. Then, Feature extraction is done by applying Fast Fourier Transform (FFT) on the filtered data. The output of the FFT provides the power spectral values. The spectral analysis of EEG during shows the frequency bands range. A dataset consisting of clean or artifact removed EEG signal obtained is fed to the Radial basis function SVM for organized training followed by testing. The Radial basis function SVM based on the training classifies all those EEG signals with abnormal indications, stating the presence of brain tumor.

##### A. Artifacts Removal

The artifacts can be informally defined as the disturbances that are likely to occur in signal acquisition and that can modify the analysis of the signals themselves. EEG (electroencephalogram) artifacts include line interference, EOG (electro-oculogram) and ECG (electrocardiogram). These noise sources greatly influence EEG analysis for acquiring clinical information. Because of this, it is essential to design specific filters to lessen the occurrence of such artifacts in EEG records. In our proposed system, we have used adaptive filtering method to remove the artifacts in EEG signal. Adaptive filters generally construct the desired output signal using the learning method.

The intent of an adaptive filter is to vary (adapt) the coefficients of the linear filter, and thereby its frequency response, to produce a signal identical to the noise present in the signal for filtering. The adaptive process encompasses the minimization of a cost function, which is used to find out the filter coefficients. In general, the adaptive filter tunes its coefficients to reduce the squared error between its output and a primary signal. The filter must converge to the

Wiener solution in stationary conditions. On the contrary, in non-stationary circumstances, the coefficients will vary with time, corresponding to the signal variation, thus converging to an optimum filter [37]. Fig.6 illustrates the typical block diagram of an EOG noise canceller using adaptive filtering.

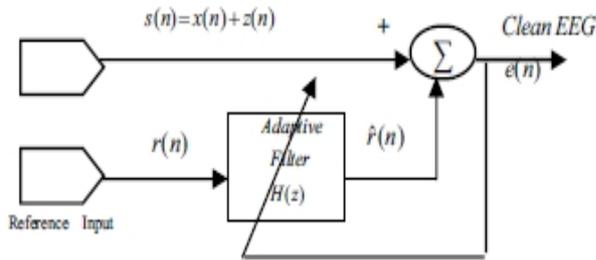


Fig. 6 EOG noise canceller system using adaptive filtering

The primary input to the system  $s(n)$  is modeled as a combination of background EEG  $x(n)$  and the effect of EOG artifacts  $z(n)$  on the EEG signal. Reference input to the system  $r(n)$  is the EOG signal picked up by an electrode. Reference input and the noise component of primary input are correlated in some unknown way.  $h(m)$  represents a finite impulse response (FIR) filter of length  $M$ . Adjusting the coefficients of the filter, the noise canceller produces an output signal  $e(n)$  which is an estimation of background EEG  $x(n)$  [27].

$$e(n) = s(n) - \hat{r}(n) \quad (8)$$

where

$$\hat{r}(n) = \sum_{m=1}^M h(m)r(n+1-m) \quad (9)$$

### B. Feature Extraction

The requirement for extracting the correct features or verifying what is "applicable information", in an EEG, which strictly associate to pathological cases with high rate of inter as well as intra- rater agreement seems to be the principal confront. Spectral Analysis methods where the chief source of solving the intricacy of extracting generic features "embedded" in an EEG signal by assuming short time stationary and study energy content of EEG channels in Conventional frequency bands adopted by human raters physicians (Delta: below 3.5 Hz, Theta: 4 -7.5 Hz, Alpha: 8-13 Hz and Beta: 13 - 40 Hz).

In our proposed system we used Fast Fourier Transform (FFT) for spectral analysis. A common use of FFT's is to find the frequency components of a signal buried in a noisy

time domain signal. The functions  $Y = FFT(x)$  and  $y = IFFT(X)$  implement the transform and inverse transform pair given for vectors of length  $N$  by:

$$X(k) = \sum_{j=1}^N x(j)w_N^{(j-1)(k-1)}$$

$$x(j) = (1/N) \sum_{k=1}^N X(k)w_N^{-(j-1)(k-1)} \quad (10)$$

where

$$w_N = e^{(-2\pi i)/N}, \text{ is a } N^{\text{th}} \text{ root of unity.}$$

After computing the Fast Fourier Transform, the absolute band power for prominent EEG spectral bands (Delta: 1-4 Hz, Theta: 4-8 Hz, Alpha: 8-13 Hz and Beta: 13-30 Hz) was calculated.

### C. Classification

With a set of features at hand, we have principally employed a supervised learning method called support vector machine classifier to classify the brain tumors from EEG signal. In specific, the Radial basis function SVM is employed to bring about efficient EEG signal classification. The input to the RBF is a clean dataset comprising of EEG signals. A part of the EEG signals is used to train the RBF for detecting possible cases of brain tumor. In testing phase, the input to the RBF is a set of clean EEG signals with/without tumor instances. The RBF evaluates the EEG signals and if any abnormal indications of tumor are felt, then the EEG signal is classified under tumor, or else it is classified as not.

## V. EXPERIMENTAL RESULTS

This section contains the results of our experiments. The proposed system is implemented in MATLAB (Matlab 7.4). The input to the system is an EEG signal recorded from patients. The EEG signal is subjected to preprocessing for removing all probable artifacts. The preprocessing results using adaptive filtering Fig (b) and FFT spectral analysis Fig(c) are depicted. Fig (d) illustrates the feature extraction process on the filtered data using spectral analysis. Subsequently, RBF predicts the clean data obtained. The experimental results demonstrate that the artifacts in the EEG signal are effectively eliminated and also an efficient classification of the recorded EEG signals is obtained.

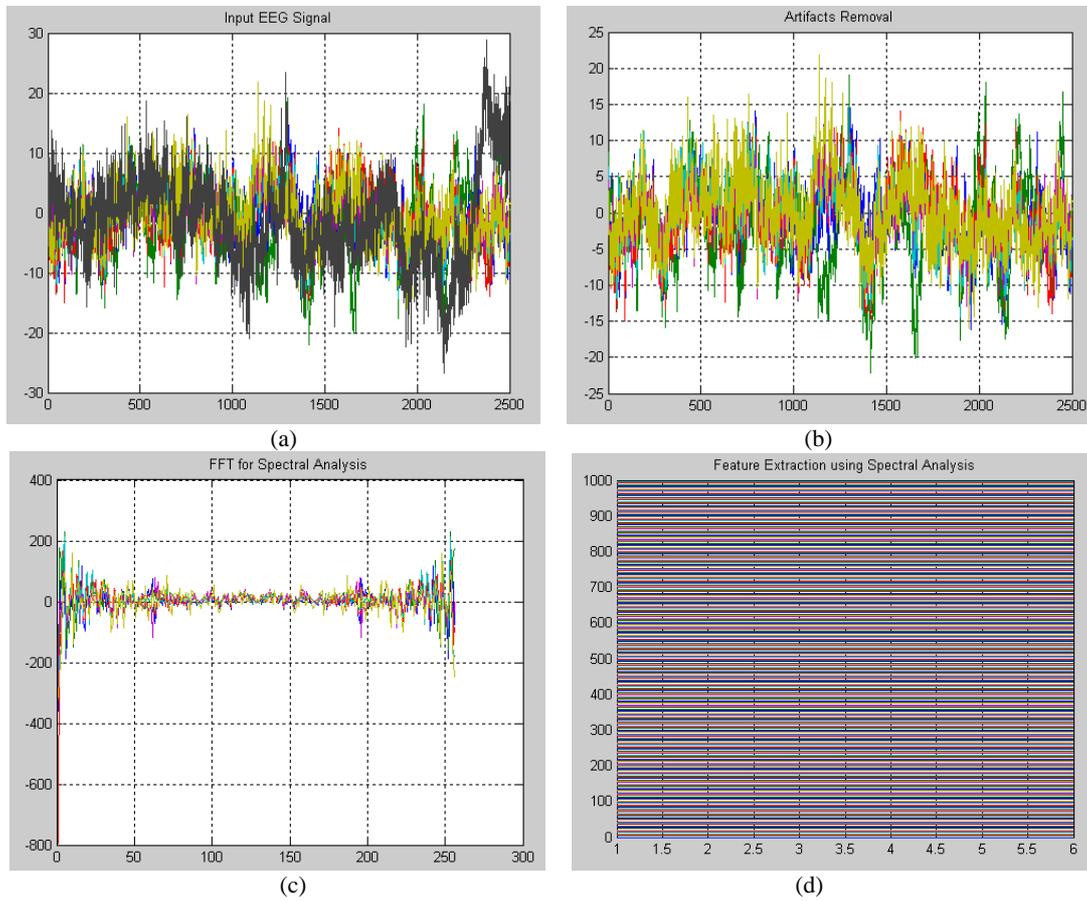


Fig. 7: output representation of brain tumor classification from EEG signal (a) Normal Input EEG signal (b) Artifacts removed EEG signal (c) Spectral Analysis Using FFT (d) Feature extracted using spectral analysis

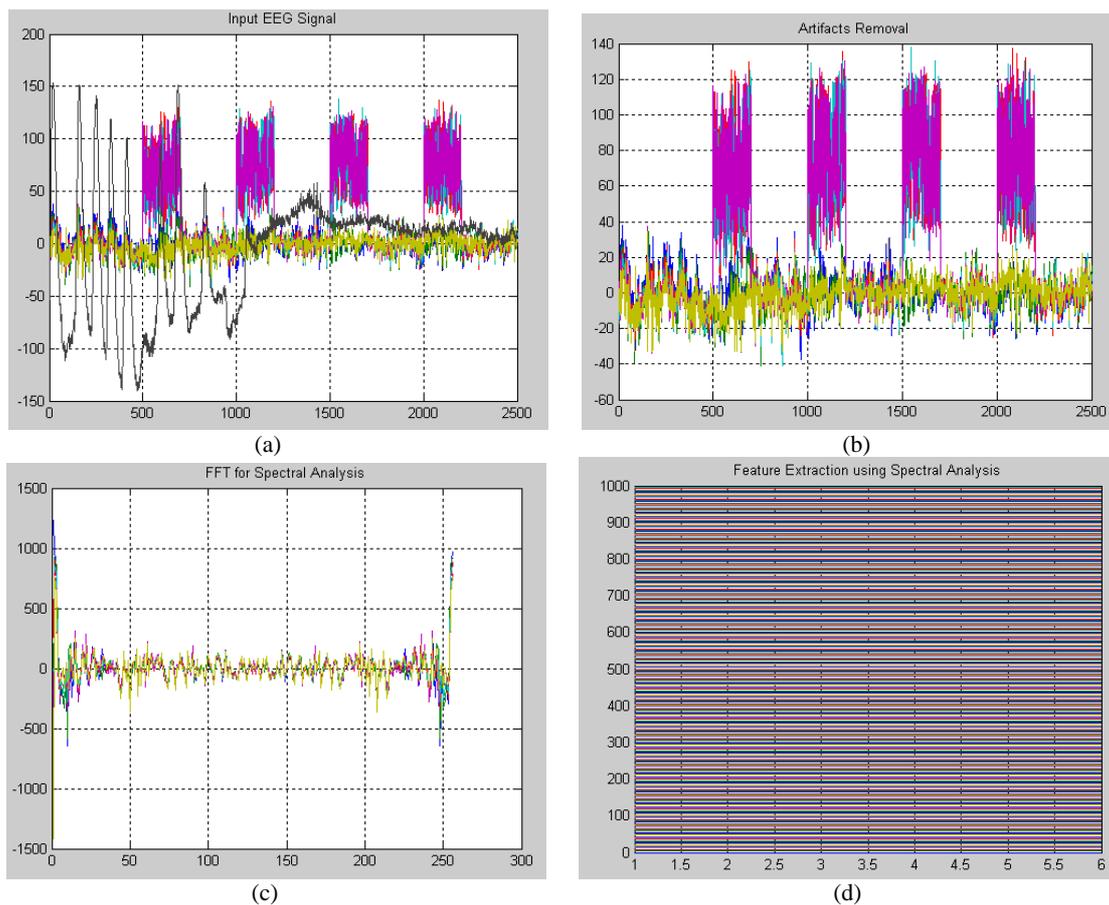


Fig. 8: output representation of brain tumor classification from EEG signal (a) Abnormal Input EEG signal (b) Artifacts removed EEG signal (c) Spectral Analysis Using FFT (d) Feature extracted using spectral analysis

## VI. CONCLUSION

Electroencephalography is a non-invasive tool that proffers millisecond temporal resolution for the study of neural mechanisms underlying mental activity. EEG signal is one of the accepted measures of brain activity that has been used immensely for clinical diagnoses and biomedical researches. In our paper we have presented an efficient classification system based on support vector machine to detect the occurrences of brain tumor in EEG signal analysis in the pre-diagnosis stage. In fact, EEG signals are highly contaminated with various artifacts, both from the subject and from equipment interferences. Added with these various kinds of artifacts, ocular noise is of the most important concern. Initially we have employed an adaptive filtering and FFT spectral analysis to remove the artifacts and feature extraction is carried out with the aid of spectral estimation using FFT. The filtered or clean EEG signals are then used in RBF initially for training and then for testing. The RBF classifies the EEG signals based on the feature extracted in spectral analysis. The results illustrate the efficiency of the artifact removal process and subsequently the classification efficiency of the proposed system.

## REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, T. M. Vaughan, "Brain-computer interfaces for communication and control", (invited review) *J. Clinical Neurophysiology Elsevier*, Vol. 113, pp. 767-791, 2002.
- [2] A. E. H. Emery, "Population frequencies of inherited neuromuscular diseases – A world survey", *Neuromuscular Disorders*, Vol. 1, No. 1, pp. 19-29, 1991
- [3] J.R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson and T. M. Vaughan, "Brain-computer interface technology: A review of the first international meeting", *IEEE Trans. on Rehab. Eng.*, Vol. 8, No. 2, pp. 164-173, June 2000.
- [4] Damien Coyle, Girijesh Prasad and T.M. McGinnity, "A Time-Frequency Approach to Feature Extraction for a Brain-Computer Interface with a Comparative Analysis of Performance Measures", *EURASIP Journal on Applied Signal Processing*, Vol. 2005, pp. 3141-3151, January 2005.
- [5] Galina N. Boldyreva, Ludmila A. Zhavoronkova, Elena V. Sharova, and Irina S. Dobronravova, "Electroencephalographic Intercentral Interaction as a Reflection of Normal and Pathological Human Brain Activity", *The Spanish journal of psychology*, vol. 10, no. 1, pp. 167-177, 2007.
- [6] S. Sanei and J. A. Chambers, "EEG Signal Processing", John Wiley & Sons, New York, NY, USA, 2007.
- [7] Kianoush Nazarpour, Hamid R. Mohseni, Christian W. Hesse, Jonathon A. Chambers, and Saied Sanei, "A Novel Semi blind Signal Extraction Approach for the Removal of Eye-Blink Artifact from EEGs", *EURASIP Journal on Advances in Signal Processing*, Article ID 857459, 12 pages, 2008.
- [8] Prabhakar K. Nayak, and Niranjana U. Cholayya, "Independent component analysis of Electroencephalogram", *IEE Japan Papers of Technical Meeting on Medical and Biological Engineering*, Vol.MBE-06, No.95-115, pp.25-28, 2006.
- [9] M. Ungureanu, C. Bigan, R. Strungaru, V. Lazarescu, "Independent Component Analysis Applied in Biomedical Signal Processing", *Measurement Science Review*, Volume 4, Section 2, 2004.
- [10] K. Lehnertz, F. Mormann, T. Kreuz, R. Andrzejak, C. Rieke, P. David, and C. Elger, "Seizure prediction by nonlinear EEG analysis," *IEEE Engineering in Medicine and Biology Magazine*, 2003.
- [11] CC Syndication, "Brain Tumors: An Overview of Symptoms, Diagnosis, and Treatment", June 27, 2006
- [12] "Brain Tumor" from [http://en.wikipedia.org/wiki/Brain\\_tumor](http://en.wikipedia.org/wiki/Brain_tumor).
- [13] Steven Pacia, MD, "Brain Tumors and Epilepsy", Fight against childhood epilepsy & seizures.
- [14] Dr. YW Fan, Dr. Gilberto KK Leung, "Management of seizure associated with brain tumor", *Medical Bulletin*, Vol. 11, No. 4, April 2006.
- [15] Rosaria Silipo, Gustavo Dero, Helmut Bartsch, "Brain tumor classification based on EEG hidden dynamics", *Intelligent Data Analysis*, Vol. 3, No.4, pp. 287-306, October 1999.
- [16] C. Majós, M. Julià-Sapè, J. Alonso, M. Serrallonga, C. Aguilera, J. Acebes, C. Arús and J. Gili, "Brain Tumor Classification by Proton MR Spectroscopy: Comparison of Diagnostic Accuracy at Short and Long TE", *American Journal of Neuroradiology* 25:1696-1704, November-December 2004.
- [17] L. Lukas, A. Devos, J.A.K. Suykens, L. Vanhamme, F.A. Howe, C. Majo's, A. Moreno-Torres, M. Van Der Graaf, A.R. Tate, C. Aru's, and S. Van Huffel. "Brain tumor classification based on long echo proton MRS signals". *Artificial Intelligence in Medicine*: 31, 73–89, 2004.
- [18] Fadi N. Karamah, Munther A. Dahleh, "Automated classification of EEG signals in brain tumor diagnostic", *Proceedings of the American control conference*, Chicago, Illinois, June 2000.
- [19] Mangano FT, McBride AE, and Schneider SJ., "Brain tumors and epilepsy", In: Ettinger AB and Devinsky O, eds. Managing epilepsy and co-existing disorders. Boston: Butterworth-Heinemann; pp. 175–194, 2002.
- [20] T. P. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne, & T. J. Sejnowski, "Removal of eye activity artifacts from visual event-related potential in normal and clinical subjects", *Clin. Neurophysiol.*, vol. 11, pp 1745-1758, 2000.
- [21] R. Verleger, T. Gasser, & J. Möcks, "Correction of EOG artifacts in event-related potentials of the EEG: Aspects of reliability and validity", *Psychophysiology*, vol. 19, pp 472-480, 1982.
- [22] W.T. Blume, M. Kaibara, and G.B. Young, "Atlas of Adult Electroencephalography". Lippincott Williams and Wilkins, Philadelphia, 2002.
- [23] Shane M. Haas, Mark G. Frei, Ivan Osorio, Bozena Pasik- Duncan, & Jeff Radel, "EEG ocular artifact removal through ARMAX model system identification using extended least squares", *Communications in Information and Systems*, 3, (1), pp 19-40, 2003.
- [24] M. Hahl, Ch. Bauer, Ch. Ziehaus, E. W. Lang, F. Schulmeyer, "Can ICA help identify brain tumor related EEG signals?", *International Workshop on Independent Component Analysis And Blind Signal Separation*, Helsinki, Finland, 19-22 June 2000.
- [25] Alexander V. Kramarenko, Uner Tan, "Effects of High-Frequency Electromagnetic Fields on Human EEG: A Brain Mapping Study", *International Journal of Neuroscience*, Vol. 113, pp. 1007–1019, 2003.
- [26] M.A.Klados, C. Papadelis1, C.D. Lithari and P.D. Bamidis, "The Removal of Ocular Artifacts from EEG Signals: A Comparison of Performances for Different Methods", *IFMBE Proceedings*, Eds.): ECIFMBE 2008, Vol. 22, pp. 1259–1263, 2008
- [27] Parisa Shooshtari, Gelareh Mohamadi, Behnam Molae Ardekani, Mohammad Bagher Shamsollahi, "Removing Ocular Artifacts from EEG Signals using Adaptive Filtering and ARMAX Modeling", *Proceedings Of World Academy Of Science, Engineering And Technology*, Vol. 11, pp. 277-280, February 2006
- [28] S.C. Ng and P. Raveendran, "Removal of EOG Artifacts Using ICA Regression Method", *In Proceedings of Biomed 2008*, N.A. Abu Osman, F. Ibrahim, W.A.B. Wan Abas, H.S. Abd Rahman, H.N. Ting (Eds.): Vol. 21, pp. 226-229, 2008.
- [29] B. Dębska and Grzegorz Iwaszek, "Prediction of physical and chemical qualities of crude-oil using statistical time series analysis", *Fresenius' Journal of physical analytical chemistry*, Springer berlin/heidelberg, Vol. 369, No. 7-8, pp. 704-708, 2001
- [30] Dunea, A.N.; Dunea, D.N.; Moise, V.I., "Cross-spectrum analysis applied to photovoltaic grids", *2003 IEEE Bologna Power Tech Conference Proceedings*, Vol. 4, pp. 6, 23-26 June 2003.
- [31] S. Deivanayagi, M. Manivannan, Peter Fernandez, "Spectral Analysis Of EEG Signals During Hypnosis", *International Journal of Systems, Cybernetics and Informatics*, pp. 75- 80, 2007.
- [32] Miroslaw Swiercz, Jan Kochanowicz, John Weigele, Robert Hurst, David S. Liebeskind, Zenon Mariak, Elias R. Melhem and Jaroslaw Krejza, "Learning Vector Quantization Neural Networks Improve Accuracy of Transcranial Color-coded Duplex Sonography in Detection of Middle Cerebral Artery Spasm—Preliminary Report",

*Neuroinformatics*, Humana Press Inc., Vol. 6, No. 4, pp. 279-290, December 2008.

- [33] B. Schölkopf, C. J. C. Burges, and A. J. Smola, *Advances in Kernel Methods: Support Vector Learning*, MIT Press, Cambridge, MA, 1999.
- [34] R. Herbrich, *“Learning Kernel Classifiers”*, MIT Press, Cambridge, MA, 2002.
- [35] J. Shawe-Taylor and N. Cristianini, *“Kernel Methods for Pattern Analysis”*, Cambridge University Press, Cambridge, 2004.
- [36] "SVM - Support Vector Machines" from <http://www.dtrek.com/svm.htm>
- [37] A Garcés Correa, E Laciari, H D Patiño, M E Valentinuzzi, "Artifact removal from EEG signals using adaptive filters in cascade", *16th Argentine Bioengineering Congress and the 5th Conference of Clinical Engineering, Journal of Physics: Conference Series*, IOP Publishing, Vol. 90, 2007.



**M. Murugesan** received his B.E (EEE) degree from GCT Coimbatore in 1997. He obtained his M.E (Applied Electronics) degree from Madurai Kamaraj University, Madurai. He has 11 years of teaching experience at college level. He worked as lecturer in the Department of EEE at Mohamad Sathak Engineering, Kilakarai. Currently he is working as Assistant Professor in EEE at Syed Ammal

Engineering College; Ramanathapuram. He is doing research in Bio-Medical Engineering under guidance of Dr. (Mrs.) R. Sukanesh at Department of ECE, Thiagarajar College of Engineering, and Madurai. His area of interest is Soft computing, Electromagnetic Theory and Communication Engineering. He is life member of IETE and ISTE.



**Dr. (Mrs.) R. Sukanesh** received her bachelor's degree B.E in ECE from Government College of Technology Coimbatore in 1982. She obtained her M.E (Communication Systems) degree from PSG College of Technology, Coimbatore in 1985 and PhD in Bio Medical Engineering from Madurai Kamaraj University, Madurai in 1999. Since 1985 she is working as a faculty in the Department of ECE at Thiagarajar College of Engineering, Madurai and presently, she is Professor of ECE and Heads the Medical Electronics Division in the same College. Her main research area includes Biomedical Instrumentation, Neural Networks, Bio Signal Processing and Mobile Communication. She is guiding twelve PhD theses in these areas. She has published several papers in International and National Journals and also published around sixty papers in International and National Conferences conducted both in India and abroad. She has delivered a number of invited lectures in various Universities. She has a Diploma in Higher Learning and has co authored a book on Gandhian Thoughts. She is life member of Bio medical Society of India, Indian Association of Bio medical Scientist and ISTE. ersity, Vietnam.