Desired EEG Signals For Detecting Brain Tumor Using LMS Algorithm And Feedforward Network

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Abstract—*In Brain tumor diagnostic EEG is the most relevant in assesing how basic functionality is affected by the lesion.EEG continues to be an attractive tool in clinical practice due to its non invasiveness and real time depication of brain function. But the EEG signal contains the useful information along with redundant or noise information. In this Paper Least Mean Square algorithm is used to remove the artifact in the EEG signal. , generic features present in the EEG signal are extracted using spectral estimation. Specifically, spectral analysis is achieved by using Fast Fourier Transform that extracts the signal features buried in a wide band of noise. The desired signal is undergone as training and testing of FLANN to effectively classify the EEG signal with Brain tumor.*

Keywords- Brain Tumor; CT; EEG; FLANN; LMS.

I. INTRODUCTION

The brain is an incredibly complex organ. The brain lives apart from and quite differently than the rest of the body. The brain contains about 10 Billion working brain cells. They are called neurons and make over 13 Trillion connections with each other to form the most sophisticated organic computer on the planet maybe even the universe. By today's computer standards, the brain far exceeds any network of linked state-of-the-art computers. Although cells in different parts of the body may look and work differently, most repair them-selves in the same way, by dividing to make more cells. Normally, this turnover takes place in an orderly and controlled manner. If, for some reason, the process gets out of control, the cells will continue to divide, developing into a lump, which is called a tumor [2].

Electroencephalography (EEG) measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a large number of neurons. 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 [4].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].

A. Techniques used for brain tumor detection

Brain tumor detection can be performed using CT, EEG [2].

a) Computer Tomography

Clinical neurologists use Computer Tomography (CT) imaging techniques for diagnosis of brain tumors because of it high accuracy in initial diagnosis of the primary pathology (96% of cases). Such scans stand short, however of analyzing the physiological functioning of the brain as a whole both at the time of initial diagnosis or as part of a long term management of the patient.

b) EEG

EEG has been used to render a clearer overall view of the brain functioning at initial diagnosis stages. In brain Tumor diagnostics, EEG is most relevant in assessing how the brain responds to treatments (e.g. post operative).

B. Research Goal

The overall research of this project is to detect the brain tumor and desired EEG signal by LMS algorithm which is part of adaptive filtering and feed forward network. 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 Least Mean Square algorithm. 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 wideband of noise. With these set of features and the clean data, we principally use ANN based on FLANN to achieve effective classification. With the aid of organized training and

testing of FLANN 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.

II.   LITERATURE REVIEW

1. Habl, M. and Bauer, Ch. and Ziegaus, Ch., Lang, Elmar and Schulmeyer, F [1] presented a technique to detect and characterize brain tumors. They removed location arifactual signals, applied a flexible ICA algorithm which does not rely on a priori assumptions about unknown source distribution. They have shown that tumor related EEG signals can be isolated into single independent ICA components. Such signals where not observed in corresponding EEG trace of normal patients.
2. Fadi N. Karameh, Munther A.Dahleh [2] focused on developing an automated system to identify space occupying lesions on the brain using EEG signals. EEG features are extracted using wavelet transform for different tumor classes and classification by self-organizing maps.

III. PROPOSED METHOD FOR BRAIN TUMOR DETECTION

We have proposed LMS algorithm for removal artifact from EEG data and Fuzzy Logic ANN to effectively classify the EEG signals with brain tumor.

A. LMS Algorithm

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 [3] is an adaptive algorithm, which uses a gradient-based method of steepest decent [10]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions.

Summary of the LMS algorithm

Input:

Tap-weight vector, $W(n)$

Input vector i.e. EEG Data, $u(n)$

Desired output, $d(n)$

Output:

Filter output, $y(n)$

Tap-weight vector update, $W(n+1)$

1. Filtering: $y(n) = W^T(n)x(n)$ (1)

2. Error estimation: $e(n) = d(n)-y(n)$

3. Tap-weight vector adaptation:

$W(n+1) = W(n) + 2\mu e(n)u(n)$ (2)

The LMS algorithm is a practical scheme for realizing Wiener filters, without explicitly solving the Wiener-Hopf equation.
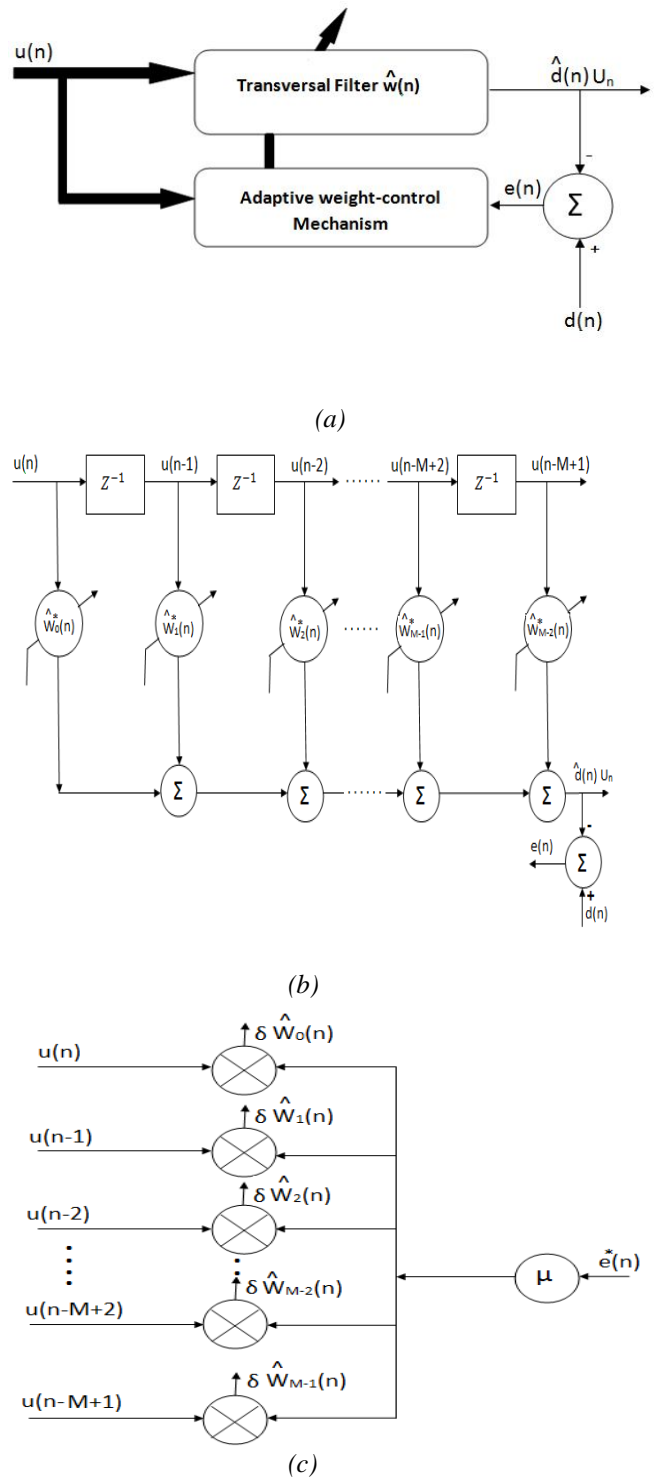

(a)

(b)

(c)

Figure 1.   (a) Block diagram of adaptive transversal filter (b) Structure of transversal filter component (c) adaptive weight control mechanism.

B. Feature Extraction Using FFT

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

C. Brain Tumor Detection Using feed forward Back propagation Neural Network with delta rule

In the proposed research, effective detection of brain tumors from EEG signals is accomplished by an ANN, feed forward back propagation neural network. The input to the feed forward back propagation neural network is clean (artifacts removed) EEG signals. The processed EEG signals are categorized into two subdivisions namely, training data and test data. The data corresponding the training phase are used to train the feed forward back propagation neural network for detecting possible cases of brain tumor. For testing, the input to the feed-forward back propagation network is an artifacts removed EEG signal with/without tumor instances. The feed forward back propagation neural network examines the EEG signals based on the trained data by a simple learning algorithm that is usually called the *delta rule*. It calculates the errors between calculated output and sample output data, and uses this to create an adjustment to the weights, thus implementing a form of gradient descent.and if any signs of tumor are identified, then the neural network notifies the presence of tumor in the EEG signal, or else not.

Feed forward Back propagation Neural Network:
A feed forward back propagation neural network is chiefly Composed of two layers, 1) hidden/first layer and
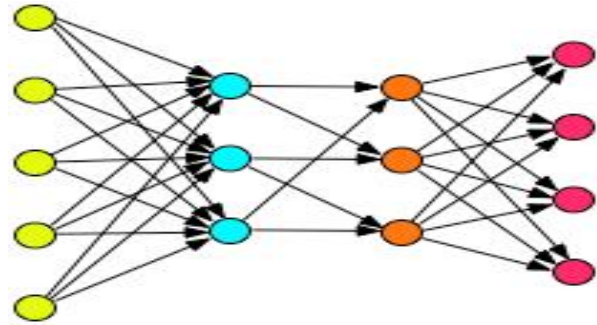2) Output/second layer.

Fig.2. Feed forward Network

The first layer has no input connections, so consists of input units and is termed the **input layer** (yellow nodes in the fig.2.). The last layer has no output connections, so consists of output units and is termed the **output layer** (maroon nodes). The layers in between the input and output layers are termed hidden layers and consist of hidden units (light blue nodes and brown nodes). When the net is operating, the activations of non-input neurons are computing using each neuron's activation function. The hidden layer has a *tan sigmoid* (tansig) activation function, and the output layer, has a linear activation function. Therefore, the first layer restricts the output to a finer range, from which the linear layer can generate all values.

IV. RESULTS AND DISCUSSIONS

This section details the detection of brain tumor. The noisy EEG data is denoised using LMS algorithm, the result shown in Fig. 3 and 4, then the feature extraction process on the filtered data using spectral analysis. With a set of features at hand, we have principally employed a supervised learning method called delta learning to classify the brain tumors from EEG signal. In specific, this is employed to bring about efficient EEG signal classification. The input to the feed forward network is a clean dataset comprising of EEG signals. A part of the EEG signals is used to train the ffn for detecting possible cases of brain tumor. The error back propagation learning algorithm is a form of supervised learning used to train m feed forward neural networks to perform the task. In outline, the algorithm is as follows:

1. Initialization: the weights of the network are initialized to small random values.

2. Forward pass: The inputs of each training pattern are presented to the network. The outputs are computed using the inputs and the current weights of the network. Certain statistics are kept from this computation, and used in the next phase. The target outputs from each training pattern are compared with the actual activation levels of the output units- the difference between the two is termed the error. Training may be pattern-by-pattern or epoch-by-epoch. With pattern-by-pattern training, the pattern error is provided directly to the backward pass. With epoch-by-epoch training, the pattern errors are summed across all training patterns, and the total error is provided to the backward pass.

3. Backward pass: In this phase, the weights of the net are updated.

4. Go back to step 2. Continue doing forward and backward passes until the stopping criterion is satisfied.

In testing phase, the input to the ffn is a set of clean EEG signals with/without tumor instances. The feed forward net 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. The result shown in fig.5 and 6.
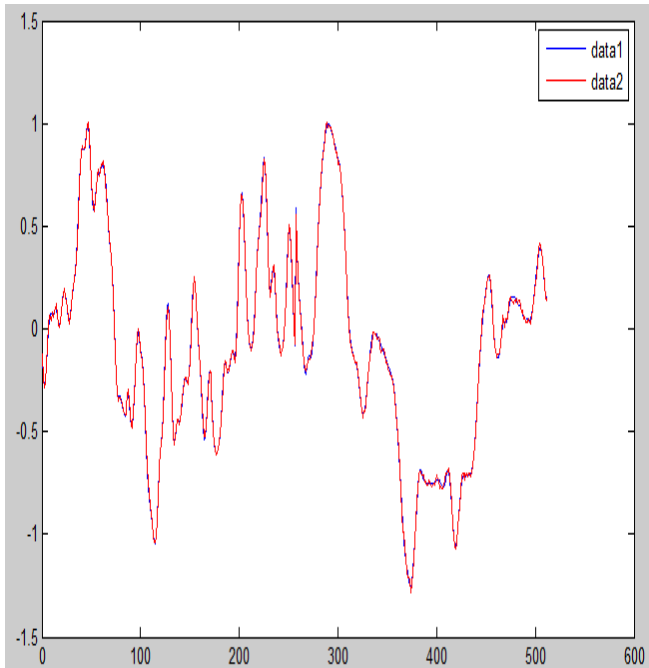

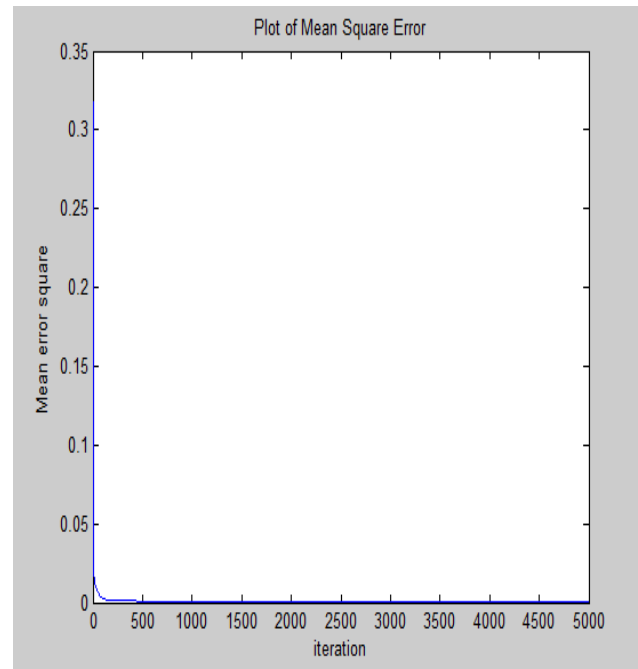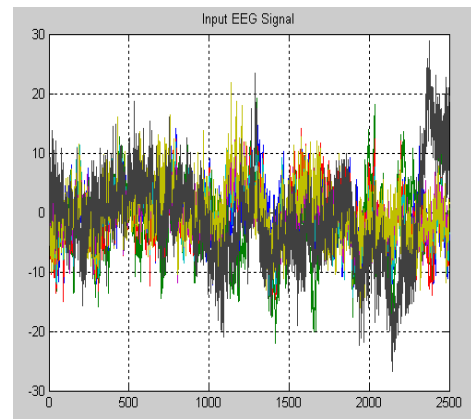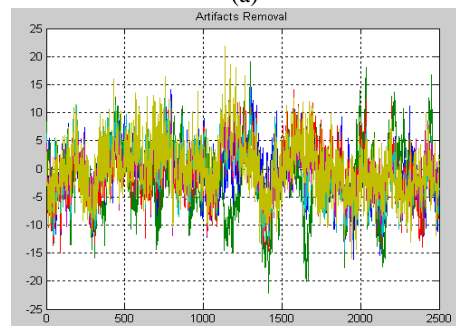Fig. 3. Shows noisy EEG signal in blue and desired i.e. artifact removed signal

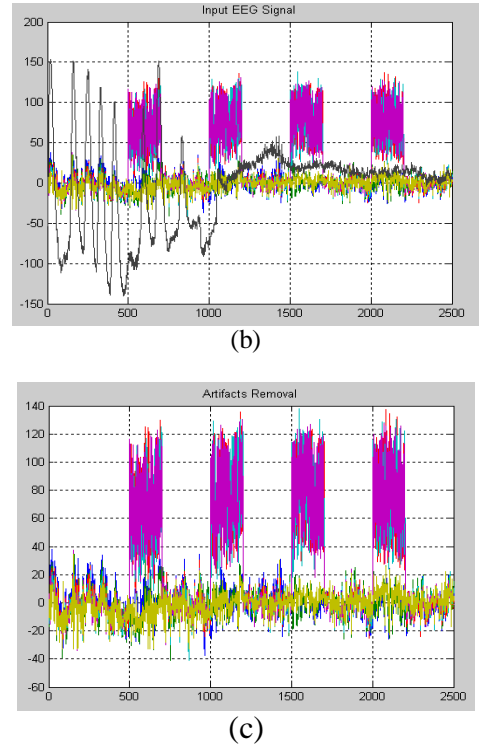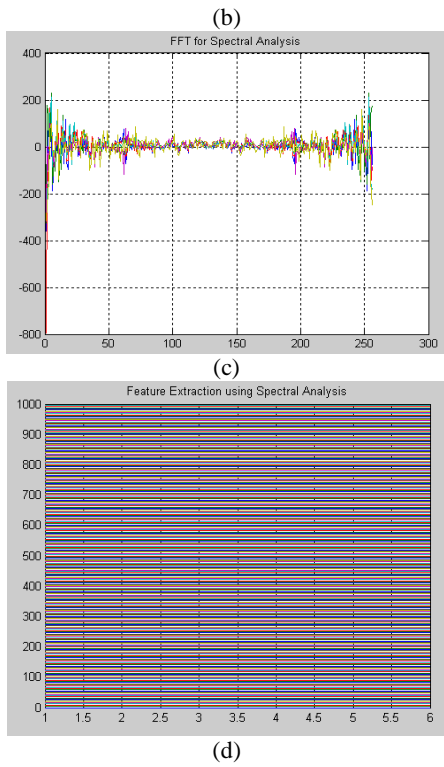Fig. 4. Showing mean square error using LMS Algorithm

(a)

(b)

(c)

(d)

Fig.5. Output representation of brain tumor detection using EEG signal (a) Normal Input EEG signal (b) Artifacts removed EEG signal (c) Spectral AnalysisUsing FFT (d) Features extracted using spectralanalys

(a)

(b)

(c)

(d)

(e)
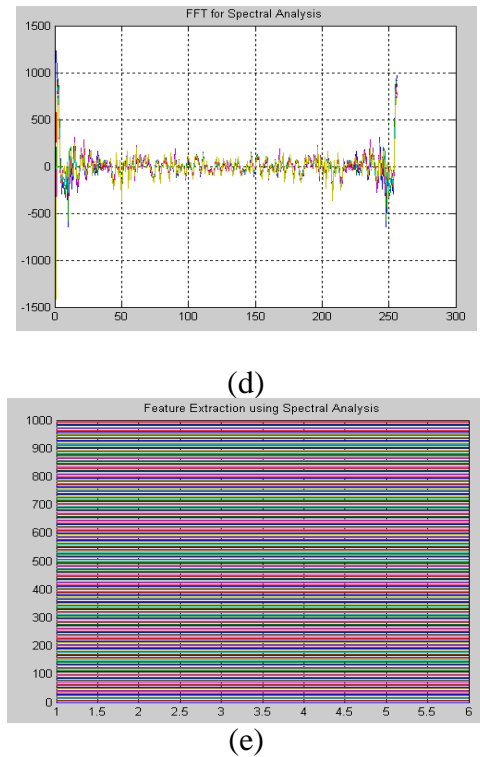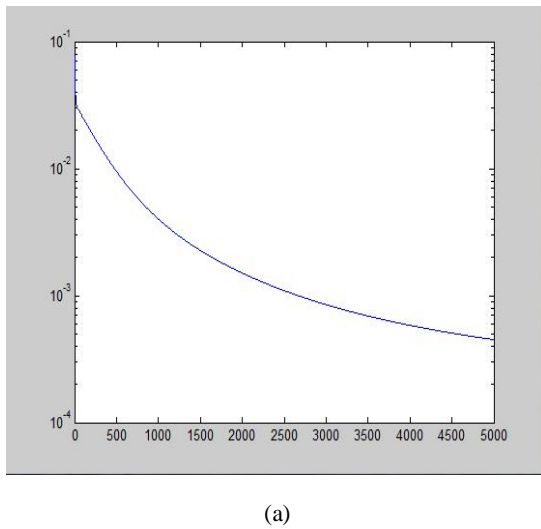
Fig.6. Results from Abnormal Input EEG signal(a)showing MSE of forward pass error of tumor EEG data(b)Abnormal input EEG data (c) Artifacts removed EEG signal (d) Spectral Analysis Using FFT (e) Features extracted using spectral analysis

Proposed method is done on MATLAB 7.8 VERSION environmet .

V. CONCLUSION

Brain tumor is one of the major causes of death. Though CT is still first option for brain tumor detection, but being a non invasive lowcost procedure EEG is the attractive one. In this paper we have presented a novel approach to remove the artifacts from EEG data and detect presence of the tumor using Least Mean Square algorithm and Feedforward network for detection of tumor. Combining these we have successfully detected the brain tumor in EEG data and classify features of EEG data. The results indicate that this proposed method can facilitate the doctor to detect the breast cancer in the early stage of diagnosis as well as classify the total cancer affected area. This will help doctor to take or analyze tumor the patient have and according to which he/she can take necessary and appropriate treatment steps. This paper is based on visual detection method of the processed EEG data. A real time system can be implemented using suitable data acquisition software and hardware interface with EEG .

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