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EEG ENHANCEMENT USING EXTENDED KALMAN FILTER TO TRAIN MULTI-LAYER PERCEPTRON

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ABSTRACT

In many applications of signal processing, especially in biomedicine, electroencephalogram (EEG) is the recording of electrophysiological brain activity along the scalp over a small interval of time and it is a biological non stationary signal which contains important information. Analysis of EEG signal is useful to identify physiological situations of the human as normal and epileptic subject. EEG signal becomes more complicated to be analyzed by the introduction of the noise. In this paper, a nonlinear Kalman Filter scheme where an extended Kalman filter (EKF) based Multi-layer perceptron (MLP) model is proposed to remove white and colored Gaussian noises from EEG recordings in physiological and pathological states (normal and epileptic). The MLP is one of the artificial neural network (ANN) models that has great track of impacts at solving a variety of problems. Activation function is one of the elements in MLP neural network. Selection of the activation function as sigmoid in the MLP network plays an essential role on the network performance. Thus, the MLP parameters as weights, and outputs are trained by an EKF in order to minimize the difference between the output of the neural network and the desired outputs. The results comparison studies are evaluated with root mean square difference (RMSD) and signal to noise ratio (SNR). The elapsed time is decreased using this method compared to normalised least mean square (NLMS) and Meyer wavelet methods. These parameters applied to EEG signals show the validity and effectiveness of the proposed approach.

Keywords: Electroencephalogram; Extended Kalman filter; Multi-layer perceptron; Noise.

INTRODUCTION

Electroencephalogram (EEG) is the recording monitoring of electrical activity along the scalp. It measures voltage fluctuation resulting from ionic current flows within the neurons of the brain.[1] EEG system usually includes non metalic electrodes such as carbon and carbon fiber. These electrodes are placed on the scalp at specific locations, determined by internationally agreed system in a typical “10/20 system”.[2]

The EEG signal can be broken down into different components. There are five components and their frequency ranges are from 0.5 to 100 Hz: (i) Delta up to 3 Hz, (ii) theta (4–7) Hz, (iii) alpha (7–12) Hz, (iv) beta (14–30) Hz and (v) gamma above 30 Hz.[3–5]

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Delta waves (δ): Delta waves frequency is up to 3 Hz. It is the slowest wave having highest amplitude. It is dominant rhythm in infants up to one year and adults in deep sleep.

Theta waves (θ): It is a slow wave having frequency range from 4 to 7 Hz. It emerges with closing of the eyes and with relaxation. It is normally seen in young children or arousal in older children and adults.

Alpha waves (α): Alpha activity has frequency range from 7 to 12 Hz, which is most commonly seen in adults. Alpha activity occurs rhythmically on both sides of the head but is often slightly higher in amplitude on the non-dominant side, especially in right-handed individuals. Alpha wave appears with closing eyes (relaxation state) and disappears normally with opening eyes/ stress. It is regarded as a normal waveform.

Beta waves (β): Beta activity is fast having small amplitude. It has frequency range from 14 to 30 Hz. It is the dominant rhythm in patients who are alert or anxious or who have their eyes open. Beta waves are usually seen on both sides in symmetrical distribution and are most evident frontally. They may be absent or reduced in areas of cortical damage. They are generally regarded as normal rhythms and observed in all age groups. These are mostly appeared in frontal and central portion of the brain. The amplitude of beta wave is less than 30 μV.

Gamma waves (γ): are the highest frequency waves with the smallest amplitude frequency and its frequency range is from 31 to 100. This band reflects the mechanism of consciousness[6] and of considerable importance in brainwave entrainment.

EEG signals became an important diagnostic tool for monitoring and managing dysfunctions and various neurological disorders of the human brain such as: epilepsy, classifying stage of sleep, seizures and brain damage.

Therefore, one of the most crutial problem in biomedical signal processing is the extraction of the high resolution EEG from contaminated recordings. This complexity is made of both pure EEG and other cerebral signals called artifacts, noise of physiological or environmental origin. Some of these artifacts are: electromygram (EMG), electrocardiogram (ECG) signal, eye blink and electrode noise. Distorted signal makes the clinical analysis and information retrieval difficult. Therefore, it is necessary to remove all such artifacts in EEG proper diagnosis. Hence, the removal of these noises leads to a number of denoising techniques and methods such as, the Meyer wavelet(dmey).[7] Learning technique,[8] averaging,[9] normalized least mean square (NLMS),[10] least mean square (LMS),[10] recursive least square algorithm with wavelet transforms (RLS with Wavelet),[11] adaptive filtering (AF) and stationary wavelet transform (SWT),[12] wavelet transform,[13] singular spectrum analysis.[14]

Machine learning techniques[8] can detect artifacts efficiently but when using this method a large amount of data is required. Averaging methods,[9] can reduce the noise levels, but it smooths the signal fluctuations. LMS[10] can reduce the noise but its algorithm needs fixed step size parameter for every iteration. As well as its excess of the mean-squared error, increases linearity with the desired signal power. This deteriorats performance when desired signal exhibits large power fluctuations and causes problem in many denoising EEG signals. The RLS algorithm[11] can reduce the noise but its difficult to implement because of its computational complexity.

The Kalman filter is a real time processing algorithm in which, is known as good linear unbiased estimator.[15–17] Its properties make it valuable in signals analysis by using the simplicity of the derived equations that can be found in Ref. 18. There are other studies where the use of Kalman filter is interesting: An off-line Kalman filter approach[19] to remove transcranial magnetic stimulation (TMS) induced by artifacts from EEG recordings is proposed. Lenz *et al.*[20] made use of a modified unscented Kalman filter and a corresponding unscented smother for the estimation of the underlying neural activity of the brain. Purdon *et al.*[21] have developed a simultaneous EEG and functional Magnetic Resonance Imaging (fMRI). Li *et al.*[22] evaluated a new robust tracking algorithm for estimating blood pressure and heart rate (HR) based upon a Kalman Filter.

Mneimneh *et al.*[23] propose an adaptive Kalman filter for the real time removal of baseline wandering using a polynomial approximation independent of the signal characteristics. Bohlin,[24] Mathieu,[25] Dusquesnoy,[26] Bleschmid[27] and Jansen *et al.*[28,29] have already applied Kalman filtering to an AR model to analyze EEG signal. In order to overcome the non linearity problem, a brooder class of Kalman filters known as the extended kalman filter (EKF) has been applied to noisy EEG data. On the other hand, EKF methods can estimate the trends of biological signals.

The EKF algorithm has also served as the basis for many neural network training algorithm studies and has been shown to be advantageous for training neural networks. This training algorithm usually converges in a few iterations and has been shown to be beneficial in many neural network training application.[30] In addition, the EKF has been used to train the Reccurent multilayer perceptron (RMLP) network by treating the weights of a network as the state of the nonlinear model.[31] Since the EKF is a second-order learning algorithm, fast convergence is expected.[32]

Recently, the EKF has been used to estimate the unknown parameters of nonlinear systems to train neural network models, i.e., the estimation of their weights.

In this paper, we propose a technique that uses the EKF to train MLP for enhancing the structure of corrupted EEG signal. This technique is used to remove different types of noise from corrupted signal.

To evaluate the proposed approach, white and colored Gaussian noises have been added to clean EEG signal. The performance metric based RMSD, SNR and elapsed time have been compared with two conventional denoising EEG techniques as Meyer wavelet (dmey)[7] and normalised least mean square (NLMS).[10]

The results of the metrics mentioned above show that the EKF-MLP can tracks the physiological and pathological states of EEG signal with different types of noises.

The paper is organized as follows: In Sec. 2, we describe the MultiLayer perceptron. Section 3 concerns the EKF to train MLP. Section 4 presents the results and discussion of this approach which is applied on EEG data sets. The conclusion is given in Sec. 5.

MATERIALS AND METHODS

Materials

The set of data was accumulated from the university of Bonn, Germany (department of Epileptology) database. Each one of this dataset [A,B,C,D] consists of twenty single channels with EEG segments of 23.6 s. The data sets A and B were measured on five healthy volunteers. These data sets consisted of segments taken from EEG recording surface using a standardized electrode placement. Volunteers were relaxed in an awake state as follows:

Set A: data was recorded with open eyes condition.
Set B: data was recorded with closed eyes condition.

Sets C and D data were measured on five patient which all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. These data sets were selected from all recordings sites exhibiting ictal (epileptic) activity, where:

Set C: data was recorded from the hippocampal formation of the opposite hemisphere of the brain.
Set D: data was recorded from within the epileptogenic zone.

All the EEG signals were recorded with the same 128 channels amplifier system, using an average common reference. The recordings were sampled at 173.61 Hz and the band pass frequency filter is 0.53 to 40 Hz of the EEG activity.[33]

Methods

Multilayer perceptron network model

A multilayer perceptron (MLP) is a variant of the original perceptron model proposed by Rosenblatt in the 1950.[34] It is probably the most often considered member of the neural network family. It consists of several layers of nodes which express artificial neural units. Each node which is connected by links with all nodes in the adjacent layer computes a weighted sum of inputs.

Assuming that we used an input layer $X = (x_1, x_2, \ldots, x_{n_0})$ with n_0 neurons and a sigmoid activation function[35]

$$f(x) = \frac{1}{1+e^x}. \tag{1}$$

The derivative of $\mathbf{f(x)}$ is easily obtained by

$$f'(x) = f(x)(1 - f(x)). \tag{2}$$

To obtain the network output we need to compute the output of each unit in each layer:

Now consider a set of hidden layers $(h_1, h_2, \ldots, h_N)$.

Assuming that n_i are the neurons number for each hidden layer h_i.

The outputs of the first hidden layer:

$$h_i^j = f\left(\sum_{k=1}^{n_{i-1}} W_{k,j}^0 x_k\right) \quad j = 1, \ldots, n_i. \tag{3}$$

The outputs h_i^j of neurons in the hidden layers are computed as follows:

$$h_i^j = f\left(\sum_{k=1}^{n_{i-1}} W_{k,j}^{i-1} h_{i-1}^k\right) \quad i = 2, \ldots, N \quad \text{and} \quad j = 1, \ldots, n_i, \tag{4}$$

where $\mathbf{W^i_{k,j}}$ is the weight between the neuron $\mathbf{k}$ in the hidden layer $\mathbf{i}$ and the neuron $\mathbf{j}$ in the hidden layer +1; $\mathbf{n_i}$ is the number of the neurons in the ith hidden layer.

The output of the ith layer can be formulated as follows:

$$h_i = (h_i^j)^T = (h_i^1, h_i^2, h_i^3, \ldots, h_i^{n_i})^T. \tag{5}$$

The network output are computed using the following equations[36]:

$$y_l = \boldsymbol{f}\left(\sum_{k=1}^{n_N} W_{k,j}^N h_N^k\right) \quad l = 1, 2, \ldots, n_{N+1}, \tag{6}$$

$$Y = (y_1, y_2, \ldots, y_{n_{N+1}}), \tag{7}$$

where $W_{k,j}^N$ is the weight between the neuron $\mathbf{k}$ in the $\mathbf{N}$**th** hidden layer and the neuron $\mathbf{j}$ in the output layer, $\mathbf{n_N}$ is the number of the neurons in the $\mathbf{N}$**th** hidden layer. The output layer vector is $\mathbf{Y}$.

The following notations are used:

N: Number of hidden layers.
$\mathbf{n_0}$: Number of neurons in input layer.
$\mathbf{n_i}$: Number of neurons in hidden layer i.
n_{N+1}**:** Number of neurons in output layer.
X: Input data of neural network.
Y: Calculated output of neural network.
h_i^j**:** Output of neuron j in hidden layer i.
$\boldsymbol{f}(.)$: activation function.

In this paper, we use an MLP of four hidden layers, five input and an output layer of four neurons (Fig. 1).

Nonlinear EEG model

The applications of nonlinear methods to the physiological sciences demonstrated that nonlinear models are useful for understanding complex systems.[37]

Furthermore the study of nonlinear MLP model is effictively applied to EEG signal to describe the nonlinear dynamic of the complex underlying behavior[38] by a mathematical model as follows:

$$x(k) = f(x(k-1)), \ldots, x(k-M), w) + u(k-1), \tag{8}$$

where $x(\mathbf{k})$ corresponds to the clean EEG signal; $\boldsymbol{u}(\boldsymbol{k})$ is the noise process. $\boldsymbol{f}(.)$ is the nonlinear function including past values of $\boldsymbol{x}(\boldsymbol{k})$.

The noisy EEG signal $y(k)$ is expressed as

$$y(k) = x(k) + v(k), \tag{9}$$

where $v(k)$ is the measurement noise.

In this work, we use the MLP for modeling the nonlinear process of EEG signal $\boldsymbol{f}(.)$.

We rewrite Eqs. (8) and (9) so that can be expressed in a state-space model:

$$x(k) = F[x(k-1)] + Gu(k), \tag{10}$$

$$y(k) = Hx(k) + v(k), \tag{11}$$

where $v(k)$ is the noise.

$$\mathbf{x}(\mathbf{k}) = \begin{bmatrix} x(k) \\ x(k-1) \\ \vdots \\ x(k-M+1) \end{bmatrix}, \tag{12}$$

$$\mathbf{F}[\mathbf{x}(\mathbf{k})] = \begin{bmatrix} f[x(k) \cdots\cdots x(k-M+1), w] \\ x(k) \\ \vdots \\ \vdots \\ \vdots \\ x(k-M+2) \end{bmatrix}, \tag{13}$$

$\mathrm{H} = [1, 0, \ldots, 0]$; $\mathrm{G} = \mathrm{H}^T$.

We assume the noise terms $u(k)$ and $v(k)$ are Gaussian white with known zero means and variances σ_u^2 and σ_v^2, respectively.

Data sampling for MLP model

The noisy EEG signal $y(k)$ was divided into many short segments (corresponding to one epoch of 20 ms) in the preprocessing stage using Hamming Window, which is defined by[39]:

$$\omega_n = 0.54 - 0.46\cos(2\pi n/N) \quad 0 \le n \le N-1. \tag{14}$$

Extended Kalman filter algorithm

The EKF is a nonlinear extension of conventional Kalman Filter that has been specifically developed for systems having nonlinear models. This algorithm deals with nonlinear data by linearizing all the nonlinear models so that the KF can be applied.[40]

The EKF algorithm model may be summarized as follows:

$$\hat{x}^-(k) = F[\hat{x}(k-1)], \tag{15}$$

$$P_{\hat{x}}^-(k) = AP_{\hat{x}}(k-1)A^T + G\sigma_u^2 G^T, \tag{16}$$

$$\text{where } A = \frac{\delta F[\hat{x}]}{\delta \hat{x}}\Big|_{\hat{x}(k-1),w},$$

$$K(k) = P_{\hat{x}}^-(k)H^T(HP_{\hat{x}}^-(k)H^T + \sigma_v^2)^{-1}, \tag{17}$$

$$\hat{x}(k) = \hat{x}^-(k) + K(k)(y(k) - H\hat{x}^-(k)), \tag{18}$$

$$P_{\hat{x}}(k) = (I - K(k)H)P_{\hat{x}}^-(k). \tag{19}$$

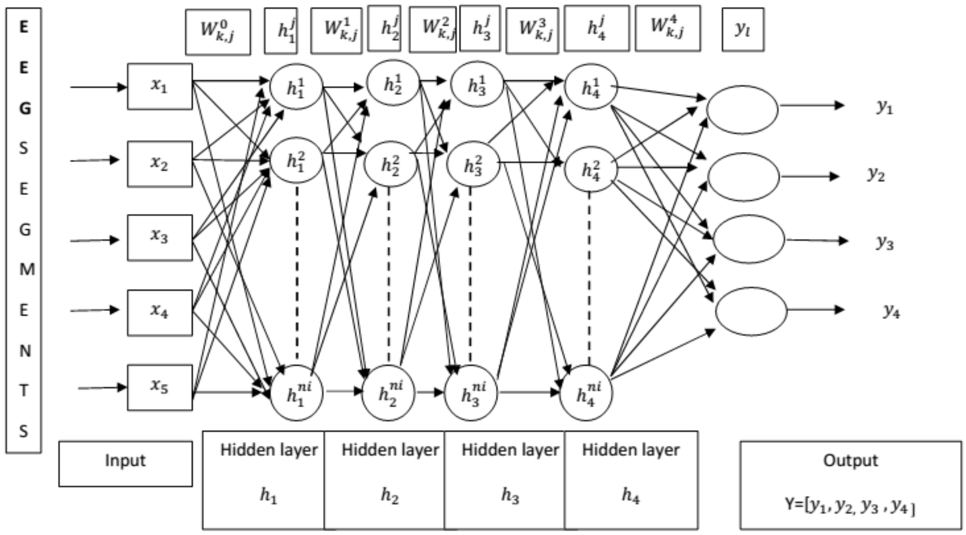

Fig. 1 Structure of a typical multilayered percteptron neural network.

EKF training MLP neural network

A typical MLP network with a four hidden layers is shown in Fig. 1. The inputs and outputs of the network are related through the connecting weights and the mapping function of $\boldsymbol{f}(.)$. To apply EKF to MLP neural network (NN), the first step is to organize all the inputs, outputs, and network weights as state vectors.

In this approach, the EKF estimates the weights of the MLPNN which in turn are used to modify the states estimates prediction of the filter. The training can then be described as a state estimation. We approach this problem by constructing a separate state-space formulation for the underlying weights as follows:

$$w(k+1) = w(k), \tag{20}$$

$$y(k) = f(w_k, x_k) + v(k), \tag{21}$$

where the state transition is simply an identity matrix, and the neural network $f(w_k, x_k)$ plays the role of a time-varying nonlinear observation on w.

The training of MLP by EKF is given by the following equations[41,42]:

$$K_{\hat{w}}(k) = P_{\hat{w}}(k)H^T(k)[H(k)P_{\hat{w}}(k)H^T(k) + R(k)]^{-1}, \tag{22}$$

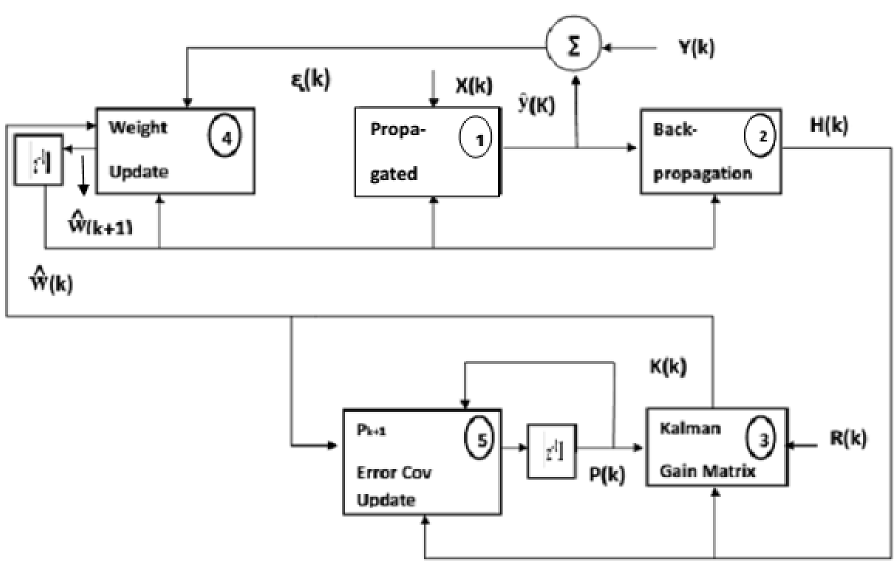

Fig. 2 Block digram for typical multilayered percteptron neural network trained by extended Kalman filter.

$$\hat{w}(k+1) = \hat{w}(k) + K_{\hat{w}}(k)\zeta(k), \tag{23}$$

$$\text{where } \zeta(k) = y(k) - \hat{y}(k)$$

$$\zeta(k) = y(k) - f(\hat{w}_k, x_k)$$

$$P_{\hat{w}}(k+1) = (I - K_{\hat{w}}(k)H(k))P_{\hat{w}}(k). \tag{24}$$

EKF training MLP involves the following steps which is shown in Fig. 2:

(i) An input training pattern $\mathbf{x(k)}$ is propagated through the network to produce an output vector $\hat{\mathbf{y}}(\mathbf{k})$. The error vector $\zeta(\mathbf{k})$ is computed by comparing the $\hat{\mathbf{y}}(\mathbf{k})$ with the reference output $\mathbf{y(k)}$.
(ii) The derivative matrix $\mathbf{H(k)}$ is obtained by backpropagation.
(iii) The Kalman gain matrix $\mathbf{K(k)}$ at time instant k is computed using the derivative matrix $\mathbf{H(k)}$, the error covariance matrix $\mathbf{P(k)}$, and the covariance noise matrix $\mathbf{R(k)}$.
(iv) The network weight vector is updated using the Kalman gain matrix $\mathbf{K(k)}$, the error vector $\zeta(\mathbf{k})$, and the current values of the weight vector $\hat{w}(\mathbf{k})$.
(v) The error covariance matrix is updated using the Kalman gain matrix $\mathbf{K(k)}$, the derivative matrix $\mathbf{H(k)}$, and the current values of the approximate error covariance matrix $\mathbf{P(k)}$.

RESULTS

In this paper an EKF based on MLP model is designed for filtering all segments of noisy EEG signals. It is based on MLP model. This nonlinear model is linearized by an EKF. The designed filter was later applied to noisy EEG signals, and the results show the filters capability in tracking and filtering noisy EEG signals. The suggested work has been successfully implemented using the MATLAB.

The entire simulation is carried out for an MLP network with four hidden layers. We evaluate the performance of the proposed EKF-MLP using two different types of patients (healthy and epileptic). The data has been sampled at Fs = 173.61 Hz.

In order to compare the three conventional methods, various performance measures have been implemented in the simulation by Matlab as are root mean squared difference (RMSD), signal-to-noise ratio (SNR) and elapsed time.

The evaluations of the EKF implemented in this paper are summarized in Tables 1–6.

As Table 1 shows the performance comparison based on various physical conditions (open and closed eyes, during and after seizure) between the proposed method and the other methods.

Table 1. Root Mean Square Difference of Electroencephalogram Signal at Different Body Conditions (White Gaussian Noise).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	31.4	23.40	19.99	122.46
DWT-dmey	26.24	56.25	23.39	255.53
EKF-MLP	67.65	57.37	69.60	315.83

Table 2. Signal to Noise Ratio of Electroencephalogram Signal at Different Body Conditions (White Gaussian Noise).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	0.00050	0.020	0.013	0.19
DWT-dmey	1.99	1.41	0.61	1.16
EKF-MLP	3.15	2.30	2.50	2.52

Table 3. Elapsed Time of Electroencephalogram Signal at Different Body Conditions (White Gaussian Noise (Second)).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	0.7789	0.8502	0.8993	0.9525
DWT-dmey	1.1357	1.5222	1.7116	1.7113
EKF-MLP	0.6394	0.6713	0.6388	0.5988

Table 4. Root Mean Square Difference of Electroencephalogram Signal at Different Body Conditions (Pink Noise).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	25.31	20.29	22.87	23.48
DWT-dmey	16.70	16.46	20.39	253.13
EKF-MLP	44.87	57.10	29.87	301.29

The effectiveness of the noise removal is quantitatively measured using RMSD[7] which is defined as:

$$\mathrm{RMSD} = \sqrt{\frac{(S_1 - D_1)^2 + (S_2 - D_2)^2 + \cdots + (S_N - D_N)^2)}{N}}, \tag{25}$$

where S is the noisy EEG signal, while D is the denoised EEG signal and N is the number of sampling points.

It can be stated from Table 1, a highest value of RMSD in all body conditions means that the filtered EEG is closer to real EEG. It is obvious that the

Table 5. Signal to Noise Ratioof Electroencephalogram Signal at Different Body Conditions (Using Colored Noise).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	0.27	0.13	0.32	0.56
DWT-dmey	1.97	1.81	3.31	2.29
EKF-MLP	2.69	2.71	3.73	2.72

Table 6. Elapsed Time of Electroencephalogram Signal at Different Body Conditions (Pink Noise (Second)).

	Healthy		Epileptic	
Methods	**Set A**	**Set B**	**Set C**	**Set D**
NLMS	0.9021	0.6965	0.6917	0.7259
DWT-dmey	1.7693	1.6333	1.6195	1.2028
EKF-MLP	0.5988	0.6388	0.6713	0.6394

EKF-MLP is more effective compared to the normalized least mean square (NLMS)[10] and Meyer wavelet (dmey) wich was implemented using the MATLAB Wavelet toolbox[7] methods.

Table 2 summarizes the Signal-to-noise ratio (SNR_{dB}) output of an EKF to train MLP and the other methods on various physical conditions (healthy and epileptic). The equation that was used for the SNR_{dB} calculation is the following:

$$\text{SNR}_{dB} = 20\log_{10}\sum_{m=1}^{N}\frac{S(m)}{S(m)-D(m)}, \qquad (26)$$

where $S(m)$ is the noisy EEG signal, while $D(m)$ is the denoised EEG signal and $m = 1, 2, \ldots, N$ where is the number of sampling points.

It can be seen from Table 2 that the results of the proposed method in all cases are better than the others. A great value of SNR_{dB} means more powerful ability to remove noise.

In Table 3, the EKF-MLP out performs the other methods. It is clear that the elapsed time of EKFMLP is less than the other methods.

Figure 3 shows the performance comparisons between the diferent methods performing under white Gaussian noise from healthy subject case based on SNR and SegSNR measures. The proposed approach EKF-MLP offers considerably better performance compared with other enhancement method.

Figure 4 shows the performance comparisons between the diferent methods performing under white Gaussian noise from epileptic subject case based on SNR and

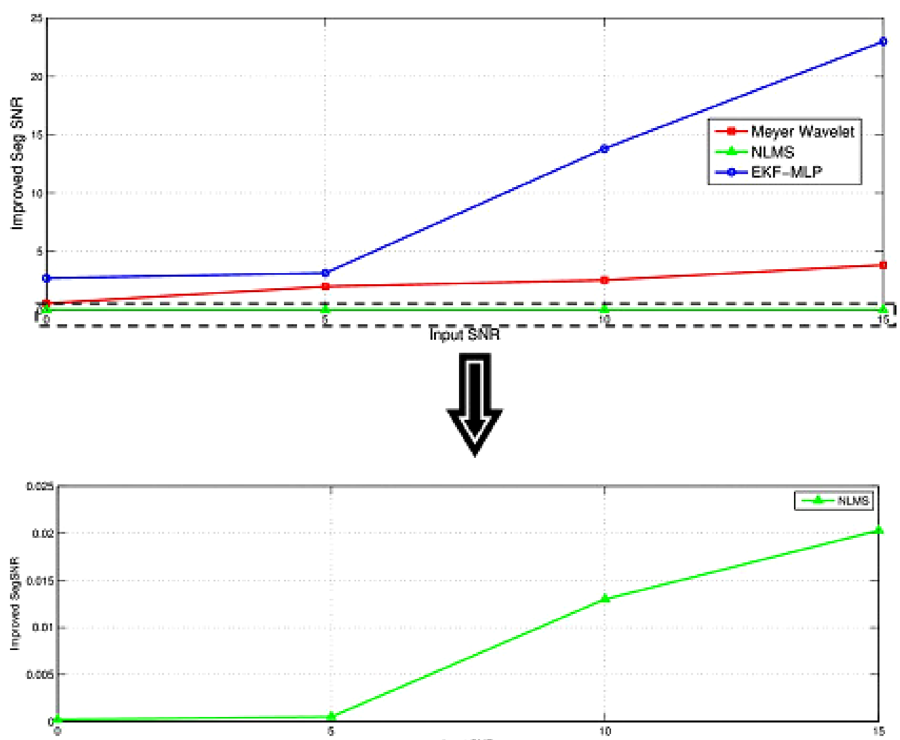

Fig. 3 Performance comparison of EKF-MLP with other EEG enhancement methods for white Gaussian noise type and various SNR levels (Healthy person).

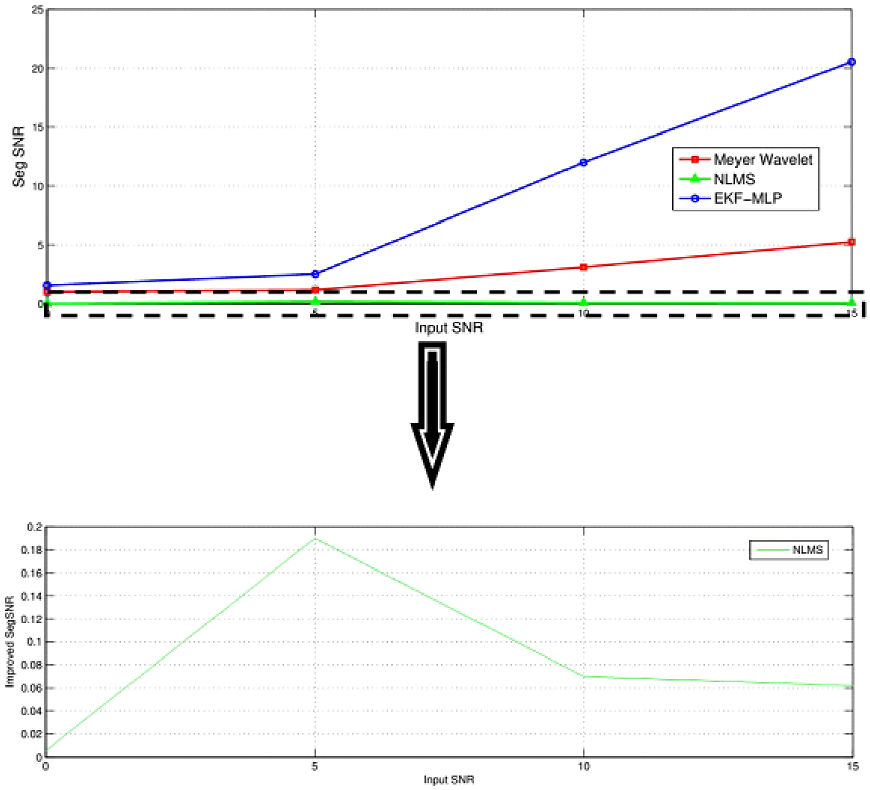

Fig. 4 Performance comparison of EKF-MLP with other EEG enhancement methods for white Gaussian noise type and various SNR levels (epileptic subject).

SegSNR measures. The proposed approach EKF-MLP offers considerably better performance compared with other enhancement approach.

Figures 5–7 illustrate the outcome of denoising approach and shows the best performance using EKF-MLP. Signal (A) provides the raw signal for healthy subject EEG, (B) noisy signal was obtained by additive white gaussian noise. This noise causes the difficulties in analyzing (EEG) and obtaining clinical information. It can be seen from Fig. 7 that Signal (C) shows the EEG signal after EKF-MLP processing. The effect of the noise on the EEG signal has been reduced and has given improved performance. This may be due to the higher degree of accuracy of the covariance estimates of the EKF.

In Table 4, the RMSD values obtained from EKF-MLP are higher than NLMS and Meyer wavelet (dmey). In terms of RMSD, higher values indicate better performance.

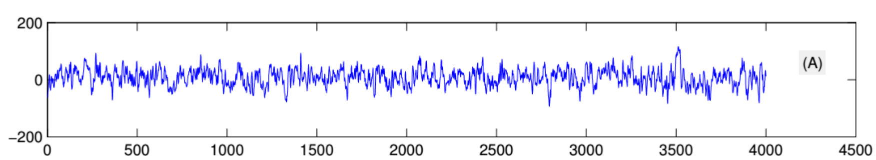

Fig. 5 Signal (A) illustrates the original (clean) signal was recorded from healthy subject.

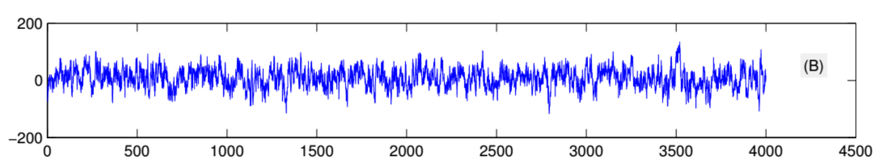

Fig. 6 Signal (B) shows the noisy signal which is obtained by additive White Gaussian noise to clean EEG signal (A).

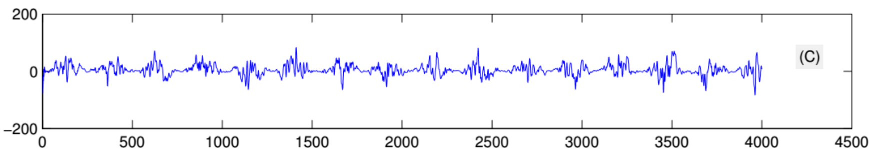

Fig. 7 Signal (C) shows the results of the output of EKF-MLP NN.

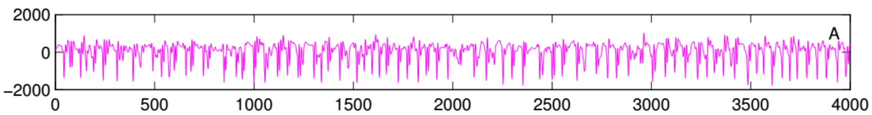

Fig. 8 Signal (A) presents the original (clean) signal was recorded from patient subject.

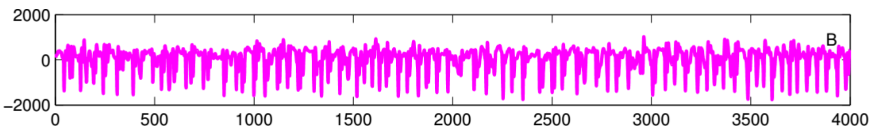

Fig. 9 Signal (B) presents the noisy signal which is obtained by additive colored Gaussian noise (pink) to clean EEG signal (A).

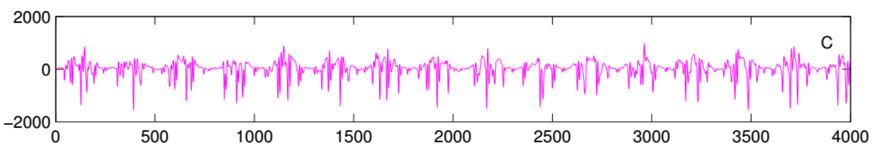

Fig. 10 Signal (C) indicates the results obtained after EKF-MLP processing.

Table 5 shows the performance of SNR_{dB} on denoising colored (pink) noise from EEG signal. EKF-MLP gives better SNR compared to other two methods.

In Table 6, the elapsed time decreases in case of EKF-MLP compared to NLMS and Meyer wavelet(dmey) methods. We can conclude that EKF-MLP is more efficient compared to others methods.

Figures 8–10 depict a raw EEG signals that contains pink noise which makes difficult to distinguish normal brain activities from the abnormal ones. As we observe from Fig. 10, C the EKF-MLP efficiently cancels the noise to produce a clear EEG signal.

DISCUSSIONS

This paper presents an approach of extended Kalman filter to train multi-layer perceptron for enhancing EEG signals corrupted by additive white and colored Gaussian noises. Precisely the EKF filter is applied to treat the weights of a network as the state of the nonlinear system. The MLP model is simulated using five inputs, four hidden layers and four outputs. The advantage of the MLP model is its ability to learn and to enhance the overall performance of the EKF filter.

The performance of the proposed method is evaluated using various parameters as RMSD, SNR and Elapsed time. The EKF-MLP method gives higher RMSD, SNR and the elapsed time is decreased compared to the normalized least mean square (NLMS)[10] and Meyer wavelet (dmey)[7] methods.

In terms of the RMSD, it can be seen from Tables 1 and 4 that RMSD values are almost similar in Set B for both white and pink noises. They are different in Set A for both white and pink noises because during the records of Set A from healthy persons with open eyes alpha wave disappears and during the records of Set B from the same healthy persons with closed eyes, alpha wave appears in the occipital lobe. We concluded that there is difference between open and closed eyes position.

The simulation results illustrate that the proposed method is very promising in nonlinear filtering, it is concluded that the performance obtained for non-linear filtering is satisfactory in terms of accuracy and reliability.

CONCLUSION

We have proposed a model based EKF to train MLP method to enhance corrupted EEG signal with additive white and Gaussian noises. The performance of the proposed Extended Kalman filtering model was compared to other applications of EEG enhancement. The results of this work approve the applicability of the extended Kalman filter based MLP for filtering noisy EEG signal. In taking advantage of training the MLP with an EKF, the proposed method (EKF-MLP) provides higher RMSD and SNR values than NLMS and wavelet meyer (dmey). The elapsed time is decreased compared to the other enhancement methods in term of computation. We conclude that EKF-MLP based noise elimination method is much faster and is an efficient processing technique for improving the quality of EEG signals in biomedical analysis.

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