ANFIS Based adaptive filter for the Elimination of Noises from the Respiratory Signals

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Abstract— **In current scenario of modern technology, we are facing a necessity of noise removal in bio medical signal processing. Various approaches are used for noise cancellation. This paper describes an intelligent adaptive filtering for noise cancellation. Here ANFIS method is being used for removal of noise from respiratory signals. Respiratory signals contaminated with various noises is taken and inspected with different membership functions. Finally using ANFIS, the original respiratory signal is restored. The major advantage of this system is its ease of implementation, faster convergence rate and minimum MSE**

Index Terms— **Adaptive filtering, Artifact, Respiratory Signal, Noise cancellation. ANFIS, Convergence rate, MSE**

Abbreviations: ANFIS, Adaptive Neuro Fuzzy Inference System, MSE, Mean Square Algorithm

I. INTRODUCTION

In clinical environment, the respiratory signal is a biomedical tool for the diagnosis of sleep apnea but it encounters various noises during data acquisition [18][19]. One of the problems in biomedical signal processing like respiratory signal processing [17]. which is the separation of the required signal from noises caused by power line interference(PLI), Electronic noise(EN), Motion Artifacts(MA), Muscle Noise(MN) and Base line wandering(BW).[4]. To remove signal components from unwanted frequency ranges by using various filters are being used. It is difficult to apply filters with fixed coefficients to reduce random noises, because human behavior is not exact known depending on the time. To overcome this problem Adaptive filter technique is required [24][25]. Respiratory Signal is the most important signals for heart activity monitoring. Interference caused by them may have technical sources [1].

NOISES IN RESPIRATORY SIGNALS:

POWER LINE INTERFERENCE (PLI)

This interference consists of 50 Hz harmonics mainly of sinusoidal signal. Parameters such as Frequency content 50 Hz with harmonics; Amplitude is 50% of respiratory signal amplitude.[10] [12] [14].

ELECTRODE NOISE (EN):

Electronic noise occurs due to the loss of contact between the electrode and skin, which is shown. It noises a random occurring rapid baseline transition, (step) which decays exponentially to the baseline value and is superimposed onto 50 Hz component.

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MOTION ARTIFICAT (MA)

Movement of the electrode away from the contact area on the skin is leading to variations in the impedance between the electrodes and skin. It causes potential variations in the respiratory signal and usually manifests itself as rapid (but continuous) baseline jumps or complete saturation for upto 0.5 seconds.

MUSCLE NOISE

It is caused by the contraction of other muscles besides the respiration activity and is shown in Figure

BASELINE WANDERING

A low frequency component disturbs the segment of the signal, which is called the baseline wandering [12] [26].

RESPIRATORY SIGNAL

The synthetic respiratory Signal wave form is shown in Fig. 1

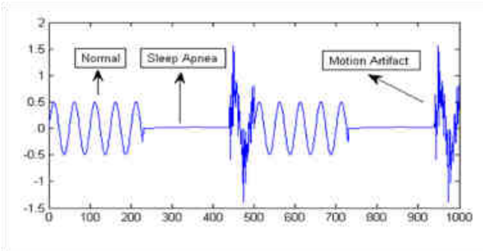

Fig. 1 Respiratory Signal[19]

NORMAL RESPIRATION

Respiration occurs in two phases: Internal, External **Internal respiration** oxygen is taken from the bloodstream into the cell and CO2 is removed from the cell into the blood stream

EXTERNAL RESPIRATION

It refers to the delivery of oxygen to the lungs so that it can be taken into the blood stream and it has two components, one is the inspiration which is the process of taking air into the lungs and another one is the expiration which expels air from the lungs Therefore, normal respiration is characterized by the presence of a certain rhythm and the presence of some energy level in the signal.

MOTION ARTIFACT

Respiration with motion artifact is generally characterized by a sudden increase in the amplitude of the signal and by a sudden variation in the rhythm of the heart usually has the higher energy when compared to the normal respiration [11].

SLEEP APNEA

Sleep apnea is diagnosable and treatable but unfortunately, current diagnostic technology is inadequate. Some of the available diagnostic modalities include overnight polysomnogram (PSG), awake imaging techniques[8].

II. METHODOLOGY

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

A neuro-fuzzy technique is called adaptive network based fuzzy inference system (ANFIS), where the fusion is made between the neural network and the fuzzy inference system that have been used as prime tools in the present work. In ANFIS, the parameters can be estimated in such a way that both the Sugeno and Tsukamoto fuzzy models are represented by the ANFIS architecture[6] .

In this proposed work, ANFIS is used as the backbone for noise cancellation in the respiratory signal. Further, the ANFIS cancelled out the interferences and provided better performance even if the complexity of the signal is very high [21][22].

ANFIS ARCHITECTURE

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs and one output. The rule base contains the rules of Takagi and Sugeno's type (if fuzzy) as follows:

If x is A and y is B, then, Z is f(x,y),where, A and B are the fuzzy set in the antecedents and Z=f(x ,y) is a crisp function in the consequent. Usually, f(x, y) is a polynomial for the input variables x and y but it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. When f(x, y) is a constant a zero order sugeno fuzzy model is formed, which may be considered to be a special case of Mamdani fuzzy inference system, where each rule consequent is specified by a fuzzy sense. The two rules based ANFIS architecture is shown in Fig.2.

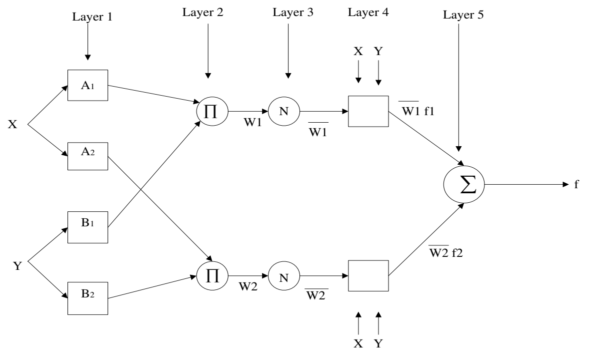

Fig. 2. ANFIS Architecture

To present the ANFIS architecture, consider two-fuzzy rules based on a first-order Sugeno model:

Rule 1: if (x is A_1) and (y is B_1), then ($f_1 = P_1x+q_1y+r_1$)

Rule 2: if (x is A_2) and (y is B_2), then ($f_2 = P_2x+q_2y+r_2$)
The circle indicates a fixed node and a square indicates an adaptive node (the parameters are changed during training).

Layer 1: Calculate Membership Value for Premise Parameter
All the nodes in this layer are adaptive nodes, which is the degree of the membership of the input to the fuzzy Membership Function (MF).

$O_{1,i} = \mu_{A_i}(x)$, for i = 1,2 or $O_{1,i} = \mu_{B_{i-2}}(y)$, for i = 3,4

Layer 2: Firing Strength of Rule
Every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y)$$

Each node in the output layer represents the firing strength of the rule. In this layer, T-norm operators are used to perform fuzzy AND can be used as the node function in this layer.

Layer 3: Normalize Firing Strength
Every node in this layer is fixed node labeled N. The i_{th} node calculates the ratio of the i_{th} rule's firing strength to the sum of all the rules firing strengths:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \qquad \textbf{For i=1, 2.}$$

For convenience, the outputs of this layer are called normalized firing strengths.

Layer 4: Consequent Parameters
Every node in this layer is an adaptive node with a node

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

where $\overline{w_i}$ is a normalized firing strength from layer 3 and { p_i, q_i, r_i } is the parameter set of this node.It is called consequent parameters.

Layer 5: Overall Output
This layer has only one node labeled as Σ, indicated, that is performing the function of a simple addition. This single node in the output layer is given by,

$$\textbf{Overall output} = O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Thus it is constructed an adaptive network that is functionally equivalent to a Sugeno fuzzy model.

COMPUTATIONS IN ANFIS

The structure of ANFIS is shown in Figure. The basic steps for computation of ANFIS is shown in Fig,3.

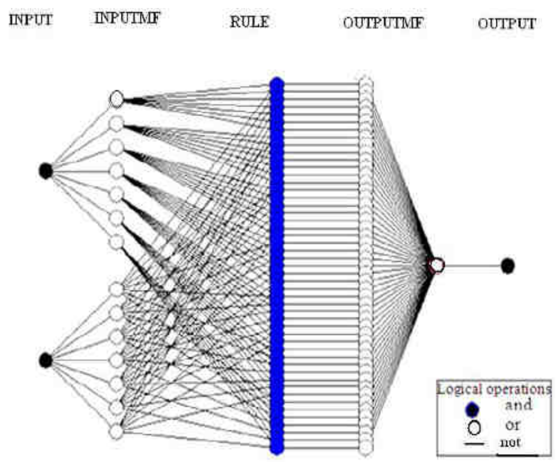

Fig. 3 Structure of ANFIS

1. Create an initial Sugeno-type FIS system using the MATLAB command genfis 1. It moves over the data in a crude way and finds a good starting system.
2. Give the parameters like number of epochs, tolerance error, number of MF, type of MF for learning.
3. Start learning process using the command envious and stop when the target is achieved or the iteration is completed. ANFIS applies the least squares method and the back propagation gradient descent for determining linear and nonlinear parameters respectively.
4. The evalfis command is used to identify the output of the FIS system for the given input. In this work, the respiratory signal as a reference signal so it acts as a training pair for ANFIS.

ADAPTIVE NOISE CANCELLATION

The method proposed in this work is Adaptive Noise Cancellation [11] (ANC) based on Neuro Fuzzy logic technique. The objective is to filter out an interference component by identifying a inear model between a measurable noise source and the corresponding unmeasurable interference. The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal through a filter that tends to suppress the noise while leaving the signal unchanged.

Fig. 4 shows the noise cancellation in ANFIS with adaptive filtering [23]. Here x (k) represents the respiratory signal which is to be extracted from the noisy signal, n (k) is the noise source signal

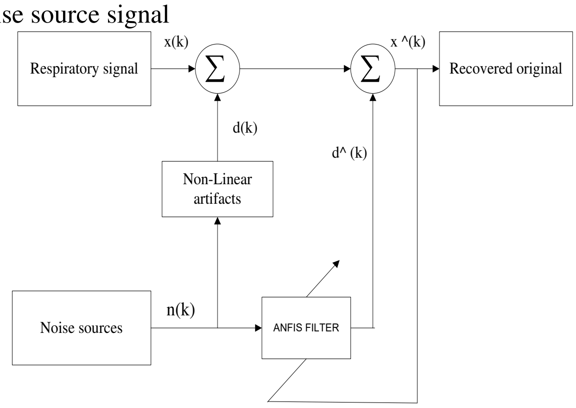

Fig. 4. ANFIS based adaptive filter[7]

The noise signal goes through unknown nonlinear dynamics and generates a distorted noise d(k), which is then added to x(k) to form the measurement output signal y(k). The aim is to retrieve the x (k) from the measured signal y(k) which consists of the required signal x(k) plus d(k), a distorted and delayed version of n (k) i.e., the interference signal.

The function f (.) represents the passage dynamics that the noise signal n (k) goes through. If f (.) is known exactly, it would be easy to recover x (k) by subtracting d (k) from y (k) directly. However, f (.) is usually unknown in advance and could be time-vary due to changes in the environment.
Moreover, the spectrum of d (k) may overlap with that of x (k) substantially, invalidating the use of the common frequency domain filtering techniques.
To estimate the interference signals d (k), we need to pick up a clean version of the noise signal n (k) that is independent of the required signal. However, it is not possible to access d (k) directly since it is an additive component of the overall measurable signal y (k). ANFIS is used to estimate the unknown interference d^ (k). When d^ (k) and d (k) are close to each other, these two get cancelled and we get the estimated output signal x^ (k) which is close to the required signal. Thus, by this method, the noise is completely removed and the required signal is obtained.

III. RESULTS AND CONCLUSIONS

The data samples are acquired from different age groups. The methods are initially with simulated data and then with real patient dataset obtained from MIT-BIH data base [16].

CLASSIFICATION OF PERFORMANCE ESTIMATION

Six performance measures are used in our work. Convergence rate, minimum mean square error, computational complexity, stability, robustness, and filter length.

CONVERGENCE RATE

The convergence rate determines the rate at which the filter converges to its resultant state.

For example, if the convergence rate is increased, the stability characteristics will decrease, making the system more likely to diverge instead of convergence to the proper solution.

MINIMUM MEAN SQUARE ERROR (MSE)

The minimum Mean Square Error (MSE) is a metric indicating how well a system can adapt to a given solution. A small minimum MSE is an indication that the adaptive system has accurately modelled, predicted, adapted and/or converged to a solution for the system.[13]

COMPUTATIONAL COMPLEXITY

Computational complexity is particularly important in real time adaptive filter applications. When a real time system is being implemented, there are hardware limitations that may affect the performance of the system.

STABILITY

Stability is probably the most important performance measure for the adaptive system. By the nature of the adaptive system, there are very few completely asymptotically stable systems that can be realized.

ROBUSTNESS

The robustness of a system is directly related to the stability of a system. Robustness is a measure of how well the system can resist both input and quantization noise.

LENGTH OF THE FILTER

The filter length of the adaptive system is inherently tied to many other performance measures. The length of the filter specifies how accurately the adaptive filter can model a given system[15].

PERFORMANCE ANALYSIS

In this section, all the simulation results are presented here using ANFIS algorithm. The respiratory signal waveform taken from respiratory database, generated noises and the corrupted respiratory signal are also shown. In this work, we have used ten data set datasets such as slp01a, slp02a, slp02b, slp32, slp37, slp41, and slp45 from MIT-BIH data base. All the simulations shown in the later parts are carried out with data no. slp37 of MIT-BIH sleep data base.

The respiratory signal waveform is shown in Fig.5.

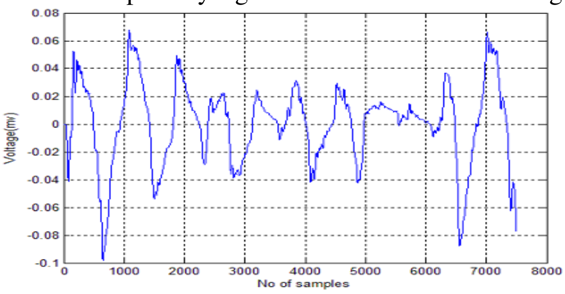

Fig. 5 Respiratory signal waveform

ANFIS based adaptive filtering technique has been proposed newly in this work and SNR values, MSE and convergence values are estimated for various noises. In order to compare ANFIS based adaptive filter we have used LMS[20], RLS and Band pass filter [1][3].Performance in terms of MSE, Improved SNR, and Convergence rate is verified through different filtering techniques for various noise sources.

ADDITION OF NOISES TO RESPIRATORY SIGNAL

The noise signals are added with the respiratory signal to get the corrupted respiratory signal. The corrupted respiratory signal is given as an input of the proposed adaptive filtering algorithm[2]. To quantify the performance of all these filters, the SNR, MSE and convergence rate are calculated and listed in Table.

Power line interference (PLI)

The power line noise is added with the respiratory signal, which is shown in Fig.6.

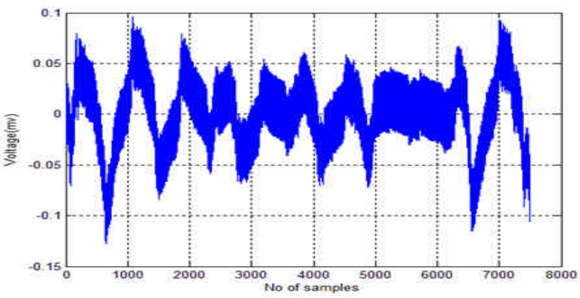

Fig. 6 . Respiratory signal corrupted by power line interference

MUSCLE NOISE (MN)

The muscle noise is added with the respiratory signal, which is shown in Fig.7.

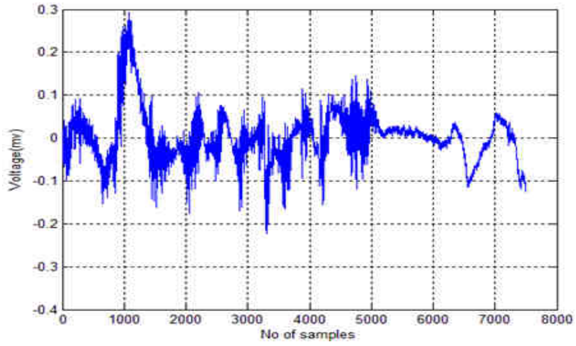

Fig . 7. Respiratory signal corrupted by muscle Noise

ELECTRODE NOISE (EN)

Fig. 8 shows the respiratory signal waveform signal containing electrode noise.

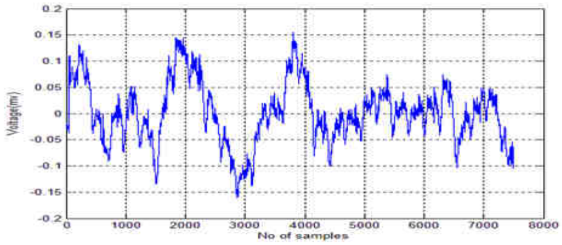

Fig. 8 Respiratory signal corrupted by electrode noise

MOTION ARTIFACT (MA)

Respiratory signal is then corrupted by motion artifact. The corrupted respiratory signal is shown in Fig.9.

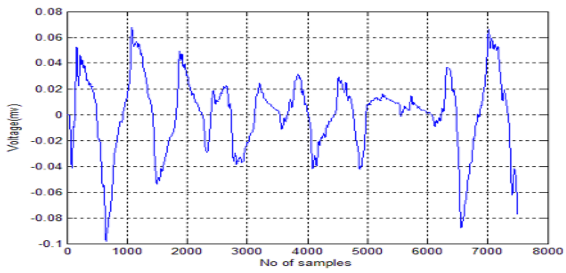

Fig. 9 . Respiratory signal corrupted by motion artifact

Baseline wandering (BLW)

Fig. 10 illustrates the performance of the respiratory signal suffering by baseline wandering.

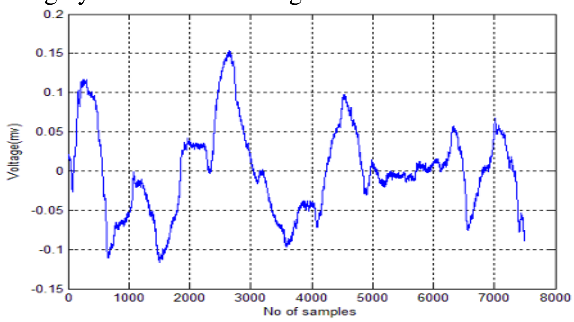

Fig. 10 . Respiratory signal corrupted by Base line wandering

PERFORMANCE ANALYSIS

In this section, all the simulation results using various filtering algorithms are presented. The respiratory signal waveform taken from respiratory database, generated noises, and the corrupted respiratory signal are also shown. In this work, datasets are considered.

ANFIS based adaptive filtering technique has been proposed newly in this work and SNR values, MSE and convergence values are estimated for various noises. Performance in terms of MSE, Improved SNR, and Convergence rate is verified through different filtering techniques for various noise sources[5]

COMPARATIVE ANALYSIS OF MSE, IMPROVED SNR AND CONVERGENCE RATE

There are different datasets used for performance analysis of adaptive filtering algorithm for various noises. The average MSE, improved SNR and convergence rate results are given in Table 1 along with standard deviation in MSE, SNR improvement and convergence rate.

Filtered output due to (a). Power line interference (b). Muscle Noise (c). Motion Artifact (d). Electrode Noise (e) Base line Wandering are shown in Fig.11.

Convergence rate for (a). Power line interference (b). Muscle Noise (c). Motion Artifact (d). Electrode Noise (e) Base line Wandering are shown in Fig.12

IV. CONCLUSION

This work throws light on the basics of respiration activity, noises corrupting the respiratory signal and enhancement of respiratory activity using various filtering algorithms. Different types of noises that corrupt the respiratory signal and their origins are discussed. For the simulations, the data sets for the respiratory signals are taken from the MIT-BIH sleep data base. The filtering algorithms proposed in this work is ANFIS, technique. The simulation results showed that the ANFIS based filtering algorithms performed better in terms of faster convergence rate and minimum MSE. It is also proved that the ANFIS based filtering outperformed conventional methods at high signal-to-noise ratio.

In this work, to record the respiratory signal, adaptive filter is used[3]. Simulations are carried out to indicate that the system is sufficiently effective in suppressing the unwanted noise signals with fast convergence. The RLS is particularly useful in the case of signals where abrupt changes of amplitude or frequency might occur such as DC noises but proved to be expensive. RLS took more time to compute, especially when the length of the filter is large. The results indicated that ANFIS would be a useful artificial intelligence technique to cancel the nonlinear interferences from the respiratory signal.

V. FUTURE SCOPE

In the future, the presented model can be implemented in a real-time environment using VLSI to design DSP processor for removing unwanted signal from respiratory signal. Conflict of Interest. The authors declare that they have no conflicts of interest

Table . 1 Comparison of average SNR, MSE, Convergence Rate

Various noises	MSE	SNR Before Filtering	SNR After Filtering	Improved SNR	Convergence Rate
Power line Interference	7.67E-06	2.75	20.38	17.63	2.17E-13
Muscle Noise	6.69E-04	4.7	13.89	9.19	2.88E-11
Motion Artifact	8.015E-04	80.23	110.48	81.23	2.44E-09
Electrode noise	1.00E-03	4.7	5.57	0.87	2.51E-13
Base line wandering(BW)	8.79E-04	3.7	6.69	2.99	2.01E-14

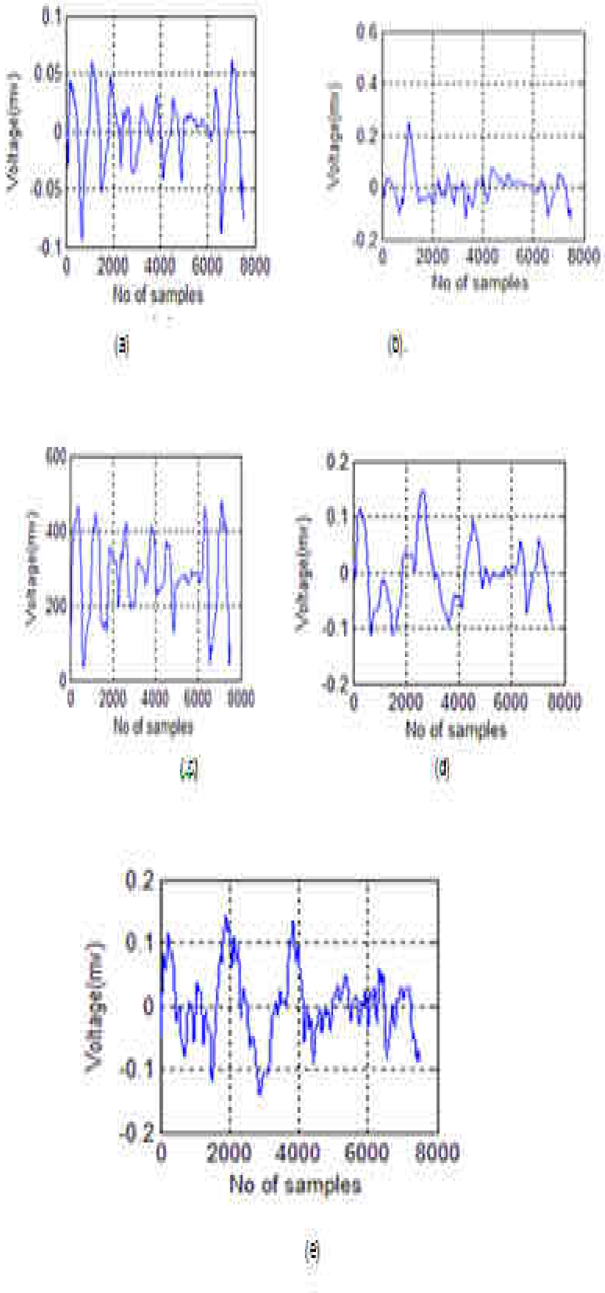

Fig. 11. Filtered output due to (a). Power line interference (b). Muscle Noise (c). Motion Artifact (d). Electrode Noise (e) Base line Wandering

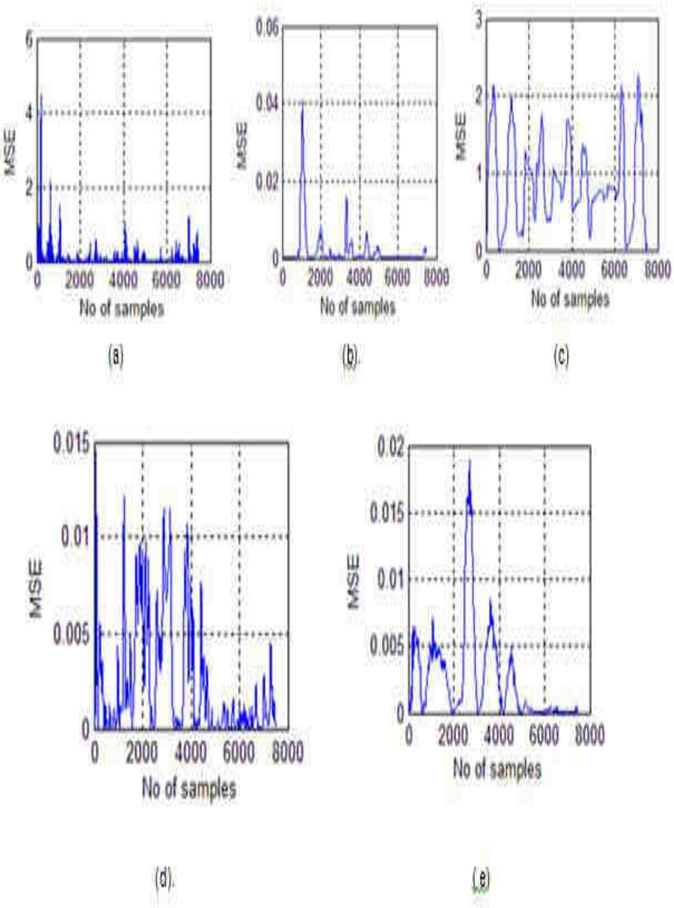

Fig. 12. Convergence rate for (a). Power line interference (b). Muscle Noise (c). Motion Artifact (d). Electrode Noise (e) Base line Wandering

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