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The Performance Analysis of Digital Filters and ANN in De-noising of Speech and Biomedical Signal

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Abstract: A huge number of algorithms are found in recent literature to de-noise a signal or enhancement of signal. In this paper we use: static filters, digital adaptive filters, discrete wavelet transform (DWT), backpropagation, Hopfield neural network (NN) and convolutional neural network (CNN) to de-noise both speech and biomedical signals. The relative performance of ten de-noising methods of the paper is measured using signal to noise ratio (SNR) in dB shown in tabular form. The objective of this paper is to select the best algorithm in de-noising of speech and biomedical signals separately. In this paper we experimentally found that, the backpropagation NN is the best for de-noising of biomedical signal and CNN is found as the best for de-noising of speech signal, where the processing time of CNN is found three times higher than that of backpropagation**.**

Index Terms: LMS, process time, error histogram, DWT and SNR.

1. Introduction

Electrocardiogram (ECG) and Electroencephalogram (EEG) are biomedical signals, used to monitor the electrical activity of the heart and brain. Biomedical signals are in the range of very low frequency (VLF) and speech signal falls in the medium range of frequency. These signals are interfered with by both low-frequency noise like hum and background noise of wide bandwidth frequency. Biomedical signals are affected by signals from other parts of the human body like the baby's heartbeat interferes with the mother's heartbeat and EEG is interfered with by ocular artifacts. These noises or artifacts of ECG/EEG need to be removed or reduced to a certain level so that signals are clean enough to detect or diagnose diseases. De-noising of speech seeks to improve the quality of speech for communications. In this paper, we employed robust de-noising techniques for ECG, EEG and speech signals.

Biomedical signals are needed for the diagnosis of various kinds of diseases, therefore enhanced signals will help the physician to detect and classify diseases precisely. Improved speech quality increases the performance of different mediums and applications. The main goal of this paper is to extract the signal with the maximum possible SNR. The paper also identifies the best suitable technique in de-noising of different types of signals. The entire theoretical analysis of section 3 and the methodology of the section 4 are implemented using Matlab-18 and corresponding results are shown in section 5 with appropriate explanations.

2. Literature Review

Some of the notable researches are marked here concerning filtering and machine learning techniques associated with the de-noising of signals. In [1], de-noising of EEG signal (contaminated by power line) is done using three types of filters: Notch, Band Stop, and LMS algorithm. First, an LF noise of 50 Hz is generated, then the noise is cured of the contaminated signal using Butterworth Band Stop filters with a bandwidth of 47-53 Hz, and an LMS filter with 10 weighting factors. The stop-band filter provides moderate results and LMS is found better than that one. In [2], a window-based Finite Impulse Response (FIR) filter is used in the de-noising audio signal. The performance of Gaussian, Kaiser, Tukey, and Target windows are compared with the proposed window function, where the SNR of the de-noised signal is found highest for the proposed window function. A similar analysis is found in [3, 4], where adaptive algorithms: LMS and RLS are used in de-noising of speech and ECG signals.

Adaptive signal processing is also applied in the de-noising of EEG signals in [5], where four artifacts are considered as (i) eye-movement activity (EOG), (ii) relative movement between scalp and electrode tip (iii) discrepancy in signal subtraction due to fluctuations in time-domain amplitude over a short period, and (iv)high amplitude contaminants. The Adaptive Noise Cancelling (ANC) algorithm solved the above problems visualized from the Power Spectral Density (PSD) of signals. Performance measurement by nullifying AC and DC signals using LMS and RLS is compared in [6].

In terms of both computational complexity and noise performance, authors in [7] suggested several systems under FIR-based DWT for comparison, where hybrid wavelet gives the best result. An improved Matrix Pencil (MP) algorithm is proposed in [8] to de-noise the Low-Frequency Oscillation (LFO) of the power system instead of the soft thresholding of DWT. Adaptive filters, LPF Butterworth filter, Notch filter, and wavelets were employed to show efficiency in noise removal in [9]. The Long Short-Term Memory (LSTM) based Batch Normalization is brought in with the help of the RNN algorithm in [10], where SNR, PSNR, and MSE are considered as the parameters of noise removal.

A combination of Modified Frequency Slice Wavelet Transform (MFSWT) and CNN is applied in [11] to detect noisy regions from wearable ECG data. The authors showed that the MFSWT-CNN combination has better results than CWT and ANN. In [12], the authors deal with the de-noising of the medical image using 'convolutional auto encoders' where performance is measured based on Structural Similarity Index Metric (SSIM) and PSNR. Here PSNR and SSIM are the highest for Salt and Pepper and lowest for Speckle noisy image.

For speech enhancement, the authors in [13] proposed the use of gated de-noising RNN, which is equivalent to neural spectral subtraction. The results of the experiments show that the suggested algorithm outperforms traditional spectral subtraction in terms of noise reduction. The authors in [14], present a novel method for de-noising speech signals that have been contaminated by fixed frequency and white Gaussian noise. A CNN model is proposed in [15] to reject very high intense noise from the ECG signals. The experiment reveals that the CNN model outperforms the LSTM model in terms of both qualities of outcomes and computing time. None of the above papers deal with three types of signal: ECG, EEG, and speech signal together for comparison. Most of the above papers work on a maximum of five methods to compare the relative performance of the de-noising techniques but this paper works on ten de-noising techniques and a comparison of techniques are shown in tabular form at the end of the result section.

3. Theoretical Analysis

Signal de-noising is the way to remove noise and artifacts from it. In this paper, we provide various techniques regarding static and dynamic filtering, DWT, the Backpropagation Algorithm of NN, Hopfield NN and CNN. All the adaptive filters, CNN, Backpropagation and Hopfield NN are supervised learning and the rest of the static filter and DWT are under unsupervised learning. This section introduces the basic theory of all the methods in a nutshell.

3.1 Digital Filters and DWT

This section provides basic concept of static filters, dynamic filters and DWT.

3.1.1. Static filter

The static filter can enhance a static signal but cannot keep pace with a real-time signal. A review of such filters is found in [16]. We used three static filters: Moving Average filter, Median filter, and Hampel filter. A moving average filter takes the mean of $M_1 + M_2 + 1$ sample, where M_1 samples on the left side and M_2 samples on the right side of the reference sample including itself found in [17]. Median Filter is a sliding window filter i.e. it moves pixel by pixel in the image and the amplitude of a pixel is replaced by the median value of neighboring pixels shown in [18]. Hampel Filter is a standard statistical filter applied in time series, where outliers are identified and replaced with representative values discussed in [19].

3.1.2. Adaptive Filter

Unlike static filters, the adaptive filter can change its parameters with the variation of signal hence suitable for real-time signal. It has two input terminals; one takes the noisy signal and the other one takes a signal which is somehow correlated with the noise. A cost function is evaluated as the mean square error (MSE) between estimated noise and the output of the filter. The weighting factors of the filter are changed to minimize the MSE. Several algorithms or supervised learning techniques are used to adjust the weight vector of the filter to minimize MSE like least mean square (LMS), *recursive least square* (*RLS*), and frequency-domain adaptive filter (FDAF) explain in [20, 21].

3.1.3. Discrete Wavelet Transform

In wavelet transform, the oscillatory function called wavelet of finite duration is used as the basis function. The transformed signal provides a time-frequency fabric of varying resolution, whereas short-time Fourier transform (STFT) gives the same result with fixed resolution. The CWT (continuous-time wavelet transform) of $x(t)$ with respect to a wavelet $\psi(t)$ is defined as [22, 23],

$$W(a,b) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{|a|}}\psi^*\left(\frac{t-b}{a}\right)dt \tag{1}$$

Where a and b are real called scaling and shift parameters and * denotes conjugation.
Inverse CWT operation can be expressed like,

$$f(t) = \frac{1}{C}\int_{a=-\infty}^{\infty}\int_{b=-\infty}^{\infty}\frac{1}{a^2}W(a,b)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dadb \tag{2}$$

where $= \int_{-\infty}^{\infty}\frac{|\psi(\omega)|^2}{|\omega|}d\omega$, $\psi(t) \leftrightarrow \psi(\omega)$ and $0 < C < \infty$

In DWT, $a = 2^m, b = n2^m, \Psi_{a,b}(t) = \Psi\left(\frac{t-b}{a}\right) = \Psi\left(\frac{t-n2^m}{2^m}\right) = \Psi(2^{-m}t-n) = \Psi_{m,n}(t)$ and instead of *a*-*b* domain, it is now transformed in the *m*-*n* domain like,

$$d(m,n) = \frac{1}{2^m}\int_{2^m n}^{2^m(n+1)} f(t)\psi(2^{-m}t-n)dt \tag{3}$$

Inverse operation of DWT is expressed like,

$$f(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} d(m,n)2^{-m/2}\psi(2^{-m}t-n) \tag{4}$$

In signal or image processing DWT is implemented as an array of filters called filter bank.

3.2 Neural Network and Deep Learning in De-noising

Although algorithms of DL and NN are mostly used in signal/image classification or recognition but in this paper, we use the concept in de-noising of the signal. Filters are suitable for the case of de-noising of deterministic signal but NN or DL are applicable for both deterministic and random signals as found in [24]. Here we apply Backpropagation, Hopfield Neural Network, and CNN in de-noising of speech, ECG and EEG.

3.2.1 Backpropagation Algorithm

The backpropagation algorithm is applied in a multi-layer perceptron network to automated complex pattern recognition applications. The nodes of the network are arranged in an array consisting of three parts: input layer, one or more hidden layers, and output layer. The input and output layer are enough for linearly separable data points but for nonlinearly separable cases one or more hidden layers is essential. Training of such ANN by backpropagation algorithm is done in three steps: (i) application input vector at the input layer which propagates to output in forwarding direction (ii) error found between the target value and output of each node propagates in backward direction (iii) adjustment of weights of each layer to alleviate the error as found in [25, 26].

3.2.2 Hopfield Neural Network

Hopfield's NN is an associative and single-layered fully connected network. It has a two-output on each processing component, one is non-inverting output to support positive weighting factor (excitatory connection when output is the same as the input) and the other is inverting terminal to support negative weighing factor (inhibitory connection when inputs differ from the output of processing element). The output of each processing element is connected back to the input terminals expect itself. In practical operation, any one of the outputs (either inverting or non-inverting) is connected back to a particular input to cope with the positive or negative weighting factor found in [27].

The weight matrix to store the pattern is denoted as **W** and expressed as:

$$\mathbf{W} = \mathbf{X}^T.\mathbf{X} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \quad (5)$$

where $\mathbf{X} = [x_1\, x_2\, x_3 \ldots x_n]$ is the input signal vector and the *i*th column of the matrix indicates the weight of *i*th output element. The weighting factor w_{ij} is positive when both the processing unit i and j are on (resembles to excitatory synapse). Again, if the unit j is not at the state of 'on' and unit i is 'on' then w_{ij} is negative. In the weight matrix elements are symmetric i.e. $w_{ij} = w_{ji}$ and the diagonal elements w_{ii} are zero.

3.2.3 CNN

Instead of multiplication of signal component and weighting factor, convolutional operation of two signals is done in hidden layers of CNN as found in [28]. The basic convolutional operation of continuous-time signals $x(t)$ and $y(t)$ is expressed as,

$$x(t) * y(t) = \int_0^t x(\tau)y(t-\tau)d\tau \leftrightarrow X(f)\,Y(f), \text{ where} x(t) \leftrightarrow X(f) \text{ and } y(t) \leftrightarrow Y(f) \quad (6)$$

For discrete-time signals,

$$x(n) * y(n) = \sum_{k=-\infty}^{\infty} x(k)\,y(n-k) = X(z)Y(z), \text{ where} x(n) \leftrightarrow X(z) \text{ and } y(n) \leftrightarrow Y(z) \quad (7)$$

It is composed of the input layer, convolutional layer, pooling layer, fully connected layer, and output layer like fig.1.

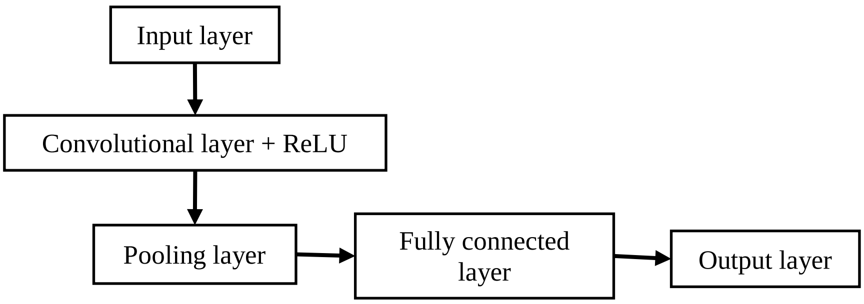


Fig. 1. basic of Convolutional Neural Network

4. Methodology

In this paper, we consider 10 different algorithms in de-noised speech and biomedical signals. After de-noising the signal, we measure the SNR of the de-noised signal and the processing time of the corresponding algorithm. These two parameters are used in the selection of an algorithm against a type of signal. In this paper we use three types of signals: ECG signal, EEG signal and Speech signal. The entire operation of the papers is visualized from fig.2. The objective of the paper is to select the appropriate algorithm of fig.2 based on the type of signal and its application.

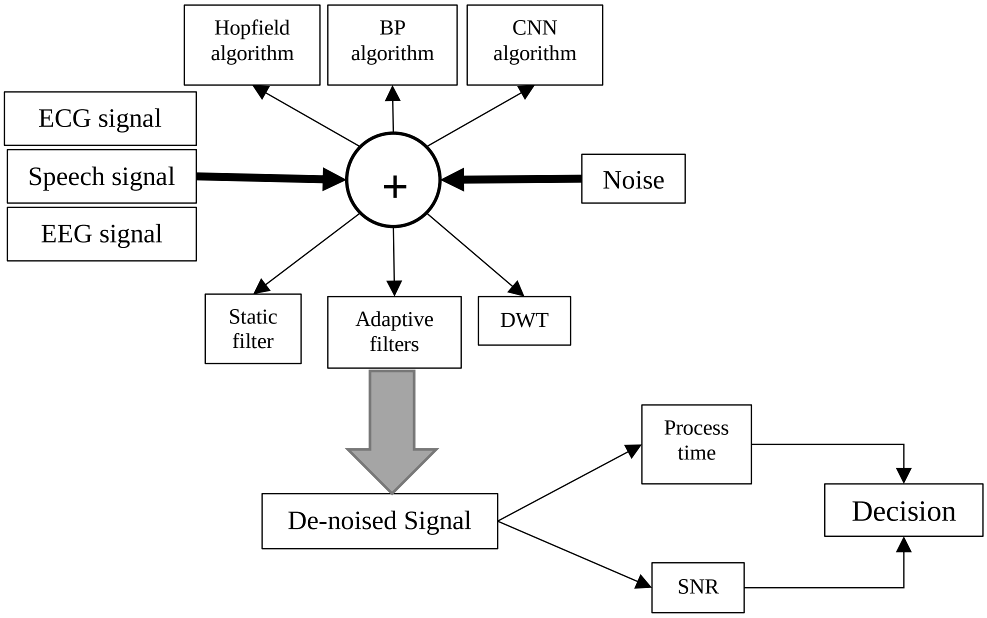


Fig. 2. Selection of algorithms

5. Results and Discussions

First of all, we consider three static digital filters: moving average, median, and Hampel filter to de-noise ECG signal. The relative performance of the three filters is shown in fig.3 in the de-noising of ECG. Secondly, we use DWT to de-noise the ECG signal under the soft thresholding technique. A comparison of original, noisy, and recovered signals under sym6 is shown in fig.4. The performance of three adaptive filters: LMS, RLS, and FDAF are shown in fig.5(a)-(c). Finally, de-noising of ECG using CNN is shown in fig.6. A similar operation is done on EEG signal shown in fig.7(a)-(d), fig.8, and fig.9. Static filter shows very poor performance on EEG signal since EEG is interfered mostly by the signal of ocular movement hence interference is more prominent compared to surrounding noise. For this reason, the static filter fails to rectify the EEG signal, and the result associated with it is excluded in this section. Next, the de-noising operation is done on speech signal and results are shown in fig.10 to fig.13 based on static filter, dynamic filter, DWT and CNN respectively like previous biomedical signal.

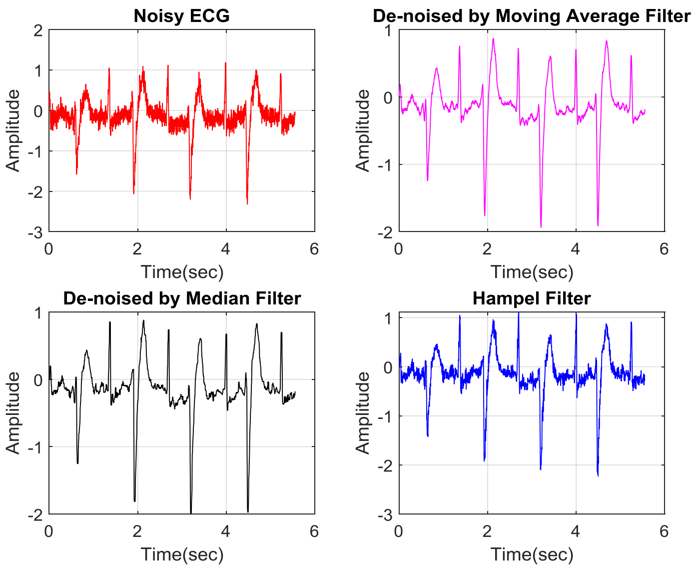


Fig. 3. De-noised ECG using static filter

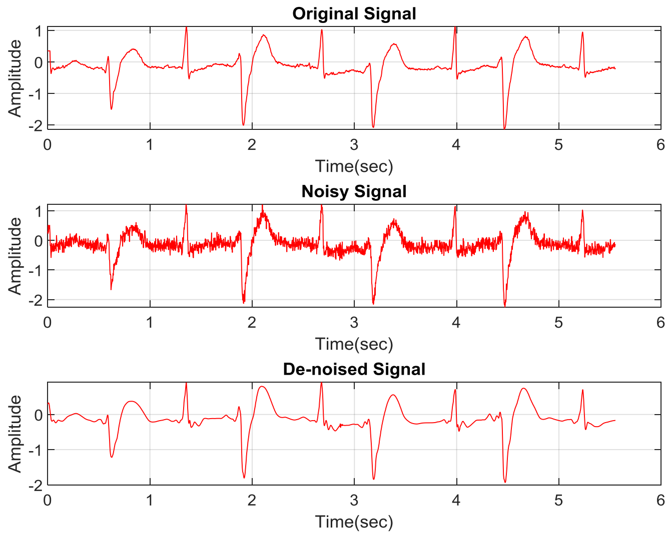
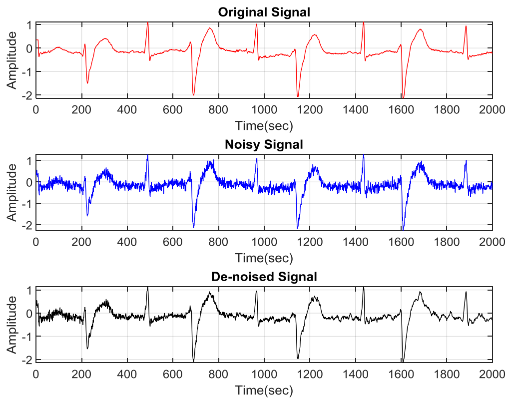
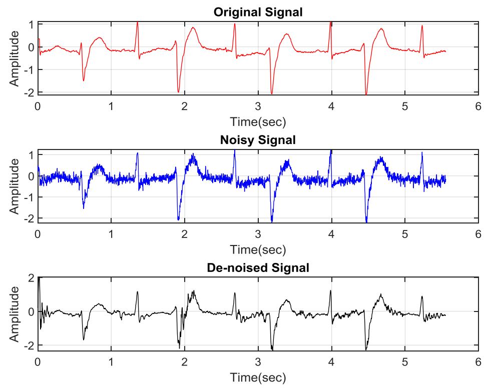


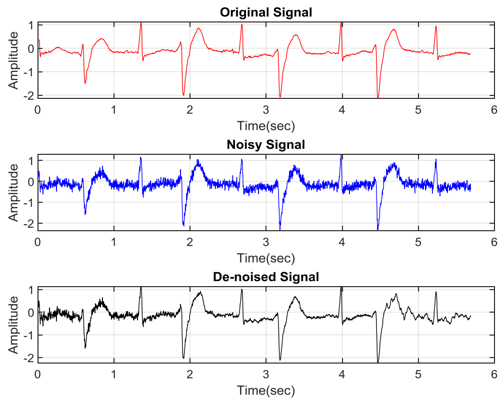
Fig. 4. De-noised ECG using DWT (sym6)



(a) LMS algorithm



(b) RLS



(c) FDAF

Fig. 5. De-noised ECG using adaptive filters

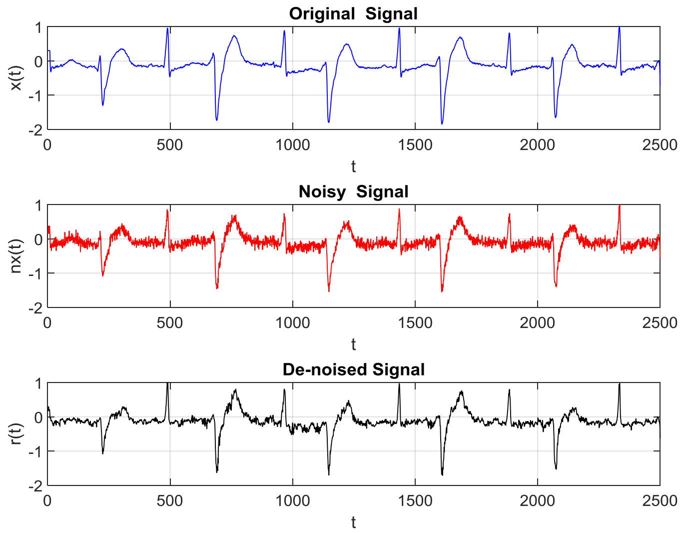
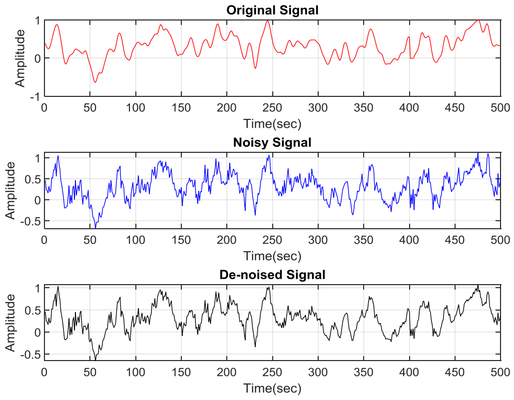
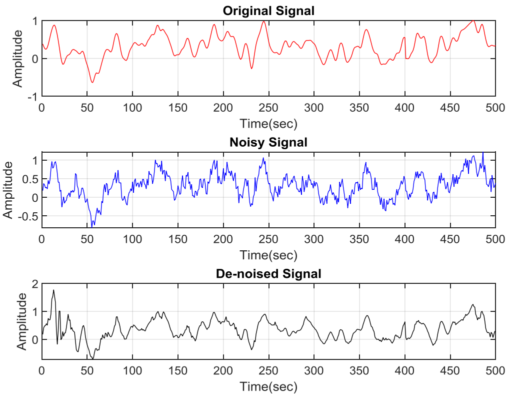


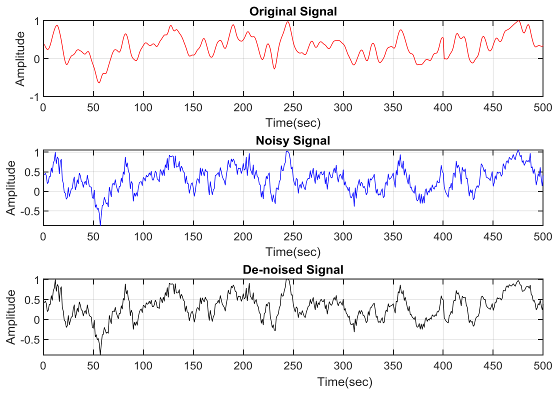
Fig. 6. De-noised ECG using CNN



(a) LMS



(b) RLS



c) FDAF

Fig. 7. De-noising of EEG using adaptive filters

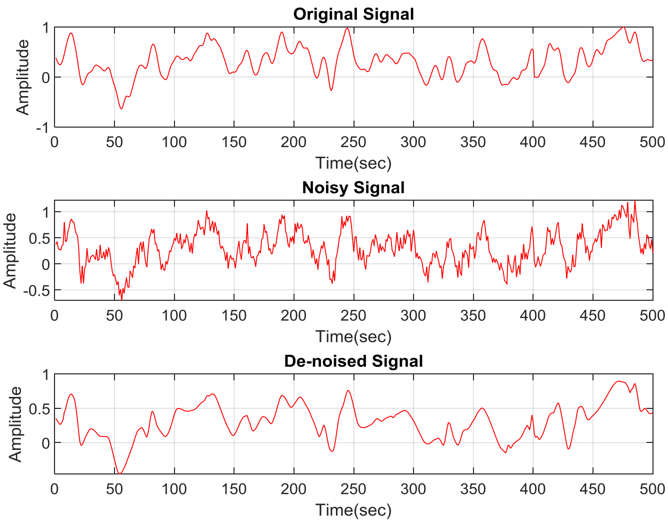


Fig. 8. De-noising of EEG using DWT (sym6)

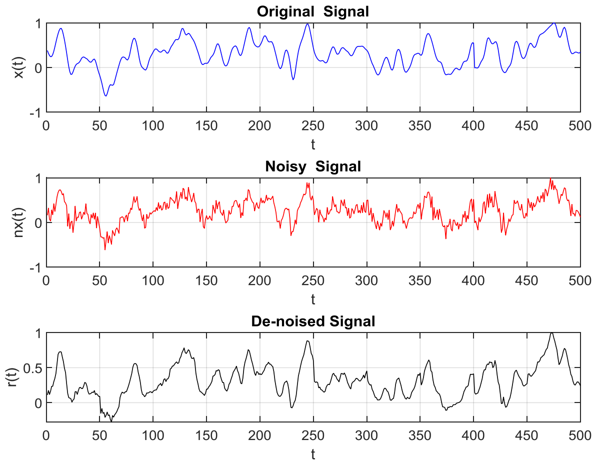


Fig. 9. De-noising of EEG using CNN

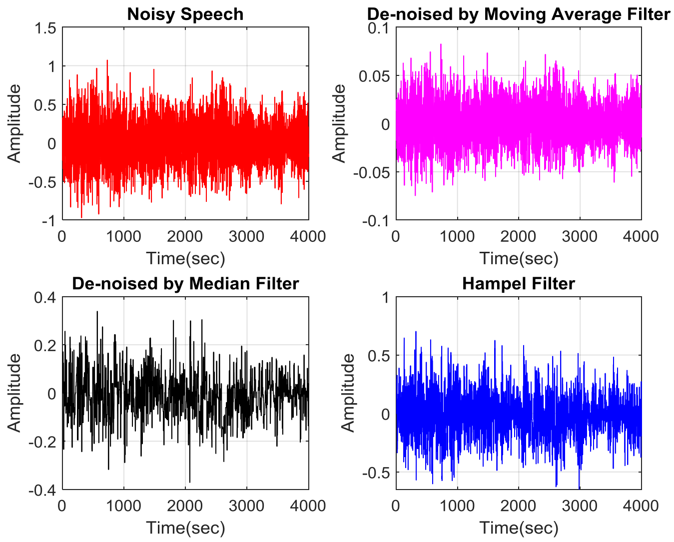
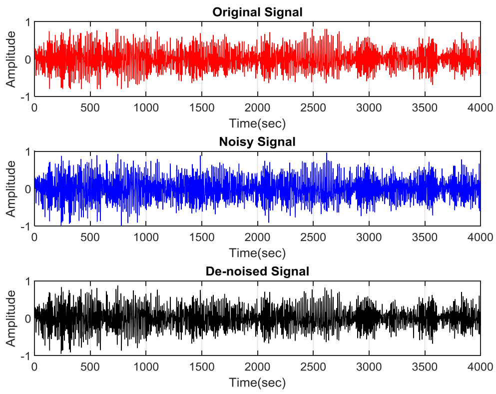
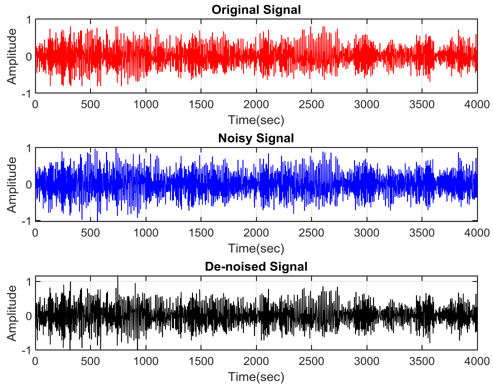


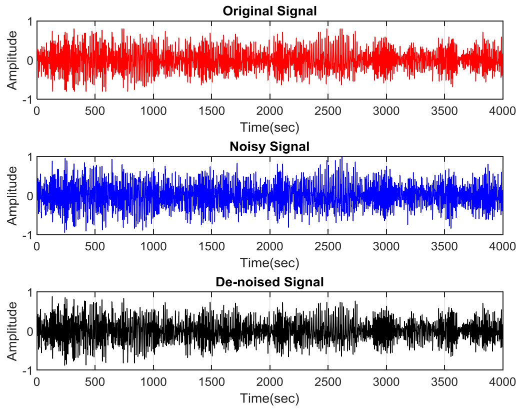
Fig. 10. De-noised speech using static filter



(a) LMS algorithm



(b) RLS



(c) FDAF

Fig. 11. De-noised speech using adaptive filters

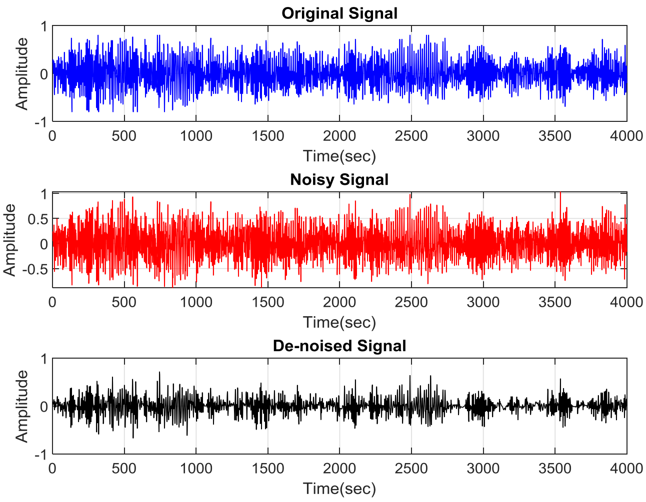


Fig. 12. De-noised speech using DWT (sym6)

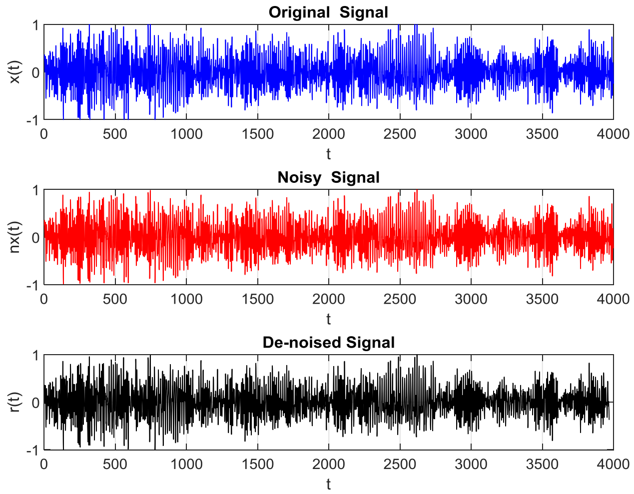


Fig. 13. De-noised speech using CNN

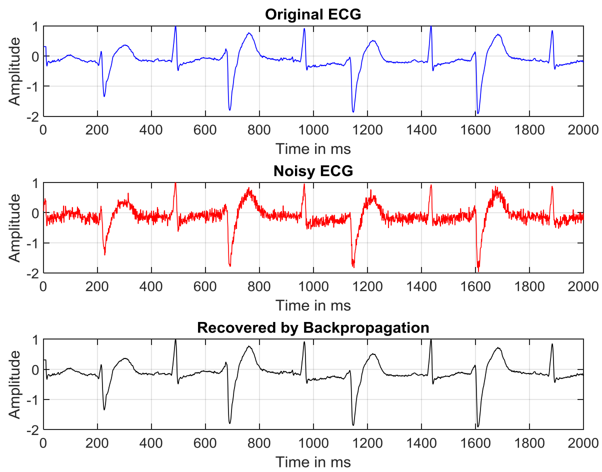
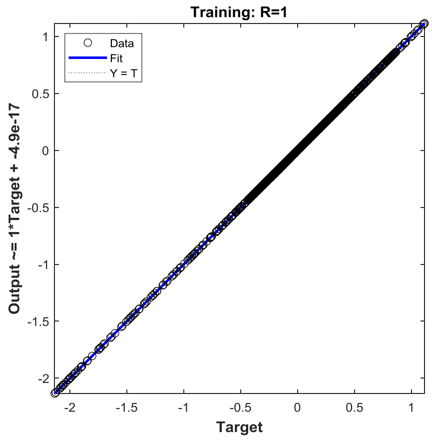


Fig. 14. De-noised ECG using backpropagation NN

(a) Error histogram



(b) Regression on data

Fig. 15. Performance of backpropagation NN for ECG signal

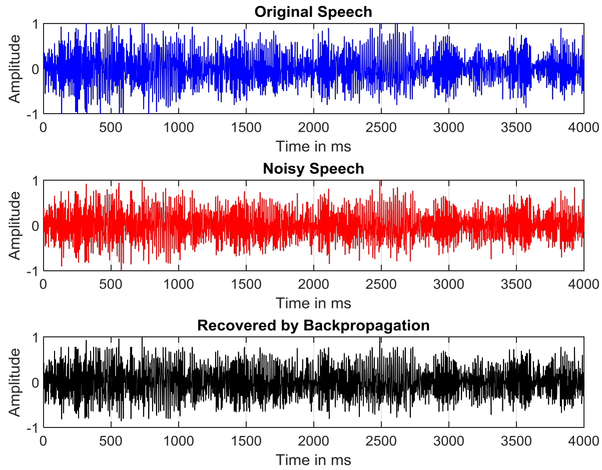
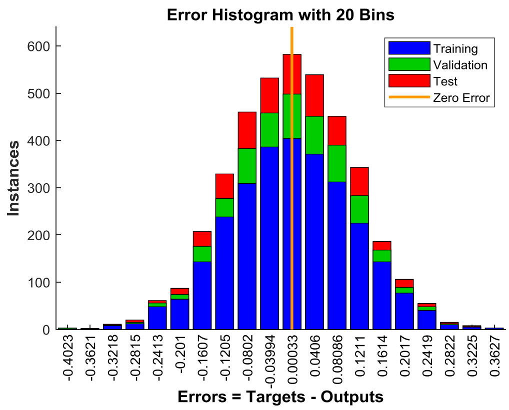
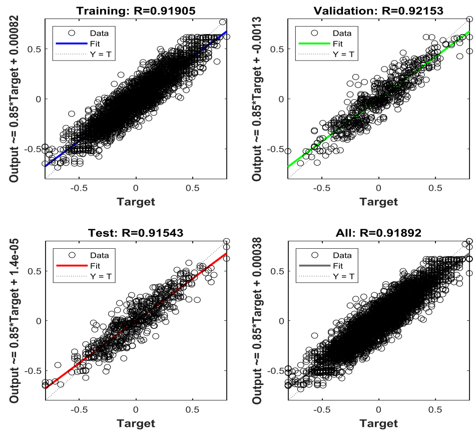


Fig. 16. De-noised speech using backpropagation NN



(a) Error Histogram



(b) Regression on data

Fig. 17. Performance of backpropagation for speech signal

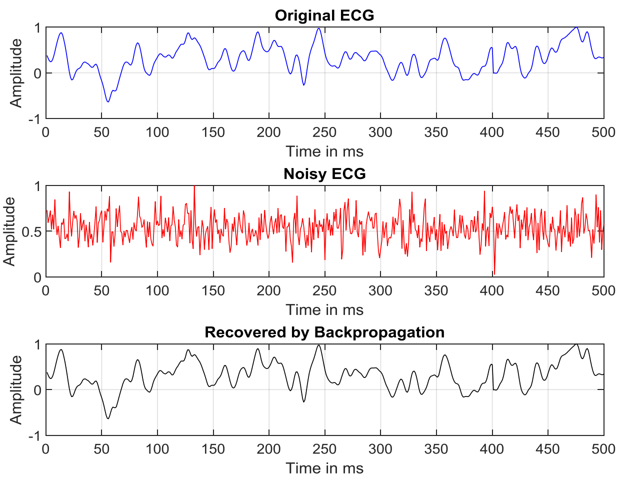
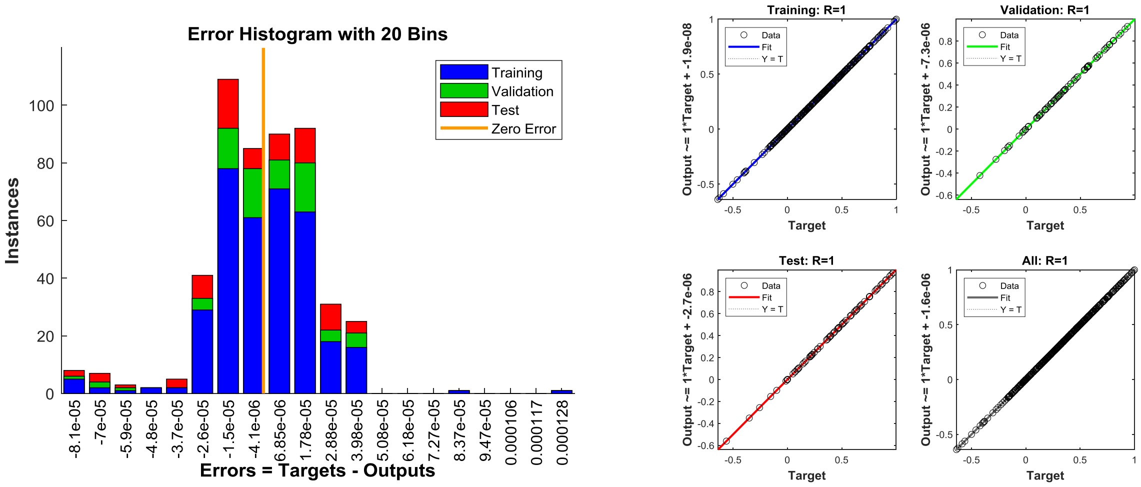


Fig. 18. De-noising of EEG using backpropagation NN (60 dB after 42 iterations)



(a) Error histogram (b) Regression on data

Fig. 19. Performance of backpropagation NN for EEG signal

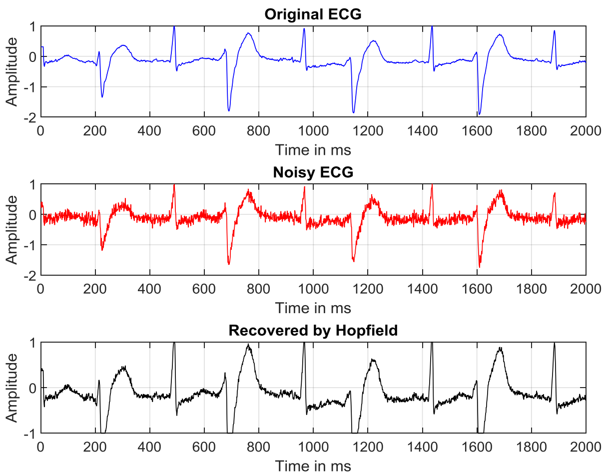


Fig. 20. De-noised ECG using Hopfield (SNR= 10.1304dB)

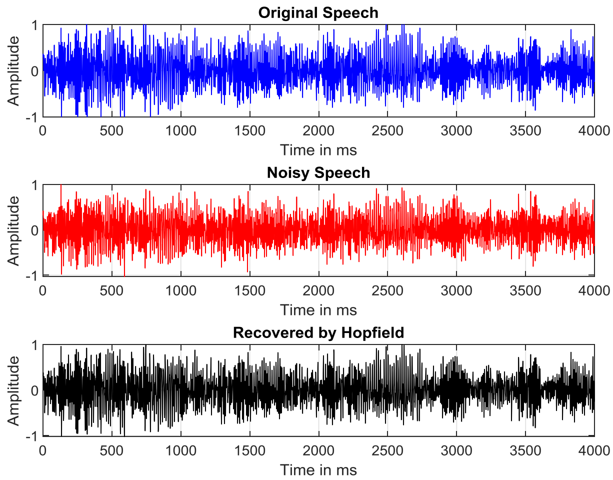


Fig. 21. De-noised speech using Hopfield (SNR= 18.1613 dB)

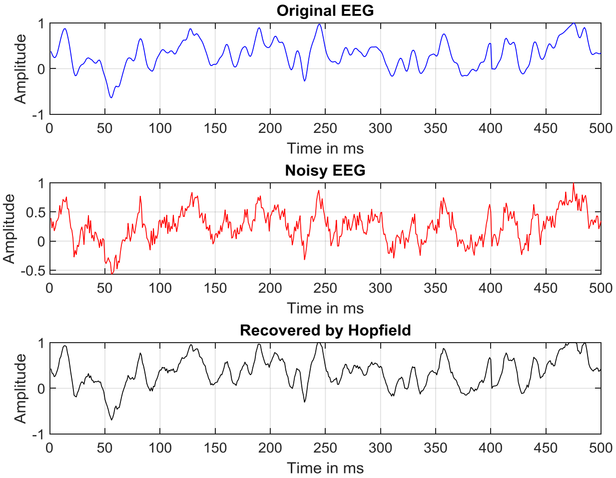


Fig. 22. De-noising of EEG using Hopfield (17.51 dB)

Finally, we include two ANNs: Backpropagation and Hopfield model to de-noise ECG, speech, and EEG signal. The Backpropagation algorithm shows very high performance in de-noising of ECG signal where the error is found almost zero visualized from recovered signal of fig.14. The error histogram and regression on data is shown in Fig.15(a)-(b). For speech signal, the Backpropagation algorithm provides moderate results visualized from Fig.16 to Fig.17. The performance of the Backpropagation algorithm is found very high for EEG signals like ECG as shown in Fig.18 to Fig.19. The reverse is true for the Hopfield model; the SNR for ECG is found 10.13 dB, that of speech is 18.1613 dB and for the case of EEG the value is 17.51dB. The de-noised ECG, speech and EEG are shown in Fig.20 to Fig.22. Considering all of the above the backpropagation NN is better for biomedical signals and the Hopfield model is found better for speech signals. The CNN provides the best result for speech signals. The processing time of backpropagation is found at 2.1563 sec to process a speech signal of 2000 samples whereas in CNN the processing time is found at 6.5313s for the same speech signal. The above result is found in a machine: Intel(R), Core (TM) i7-1065G7, clock: 1.30GHz-1.50 GHz, RAM: 16.0 GB, 64-bit OS using Matlab 18. Therefore, for the real-time operation, we can choose backpropagation NN and for the offline system, CNN is the best choice.

Table 1. SNR of the de-noised signal

Signal	Filter	SNR(dB)	Signal	Filter	SNR(dB)	Signal	Filter	SNR(dB)
ECG	Moving average	5.370	Speech	Moving average	Poor<1	EEG	Moving average	Poor<1
	Median Filter	4.552		Median Filter	Poor<1		Median Filter	Poor<1
	Hampel	3.953		Hampel	Poor<1		Hampel	Poor<1
	DWT	15.051		DWT	4.304		DWT	12.61
	LMS	14.928		LMS	14.439		LMS	14.2587
	RLS	8.893		RLS	8.8828		RLS	8.2529
	FDAF	14.333		FDAF	13.573		FDAF	14.0249
	CNN	10.452		CNN	21.159		CNN	11.228
	Backpropagation	19.552		Backpropagation	10.23		Backpropagation	17.672
	Hopfield	10.134		Hopfield	18.161		Hopfield	17.513

The relative performance of 10 operations is shown in Table 1 in the context of SNR in dB. The remaining part of the result section gives comparative performance of all algorithms used in this paper. In the case of ECG signal, DWT, LMS, FDAF, and Backpropagation reveal very high performance; CNN and RLS show moderate performance and static filters show the lowest level of performance. In the case of speech signal CNN is the best, adaptive filters and Hopfield model show moderate results. The static filters are the worst of both speech and EEG cases. For EEG signal DWT, LMS, FDAF, and Backpropagation provide high performance, CNN and RLS show moderate performance and static filters show the lowest level of performance like ECG. Actually, the entire results of the paper are visualized from Table 1. Finally, working on 2000 samples of EEG, the CPU time difference is found 9.88 seconds for CNN and that of backpropagation is 3.76 seconds under Matlab 18.

6. Conclusion and Future Work

De-noising signal plays a vital role in all applications of signal and image processing. This paper deals with several de-noising techniques on biomedical and speech signals hence giving the guideline to select the appropriate model. In case of static system, we can use CNN but for real-time system backpropagation NN is preferable. Here, we only consider random noise and decide on the selection of the best de-noising algorithm. In the future, we will consider the Additive White Gaussian Noise (AWGN) of [29] (applicable in wireless communication) as the source of noise and apply all the algorithms to observe whether the same or different algorithm is appropriate for both random noise and AWGN. We will also apply all the algorithms in de-noising of digital images and we can include salt and pepper noise, Speckle Noise, Gaussian noise, and Poisson noise.

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