Noise - Canceller based on Generalized-Mean Neural Networks

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Abstract

Noise cancellation in the field of Adaptive filtering has become the essential requirement of the signal processing .The standard multilayer perceptron (MLP) model of Neural Networks is now popular in Adaptive filtering This paper presents the noise-cancellation technique based on Generalized-mean neuron network (GMN). This network consists of an aggregation function, which is based on the generalized mean of all the inputs applied to it. Performance of this GMN network is also compared with traditional MLP networks. The simulation results show the GMN network can be suitably applied for the signal detection.

Keywords: Noisy signals, Noise canceller, Generalized- mean neuron, function approximation

1. Introduction

Adaptive filtering is used in a variety of applications like channel equalization, active noise cancellation, echo cancellation etc. involving time- varying signals and systems. Applications of Neural Networks are becoming very popular and well known for the Adaptive filtering [1]. The probabilistic search algorithm and simulated annealing has been applied in this field of signal processing [7]. Recently non-linear and adaptive filtering has been developed for noise free signal detection extensively. The noise canceller based on Neural Network provides better noise-cancellation capability.

In this paper we present noise-cancellation by neural network using new neural architecture i.e. **Generalized-Mean Neuron (GMN) model**. This new model consists of an aggregation function, which is based on the generalized mean of all the inputs applied to it [2]. The resulting neuron model has the same number of parameters with improved computational power as the existing multilayer perceptron (MLP) model [2].

GMN model based noise-canceller presented by author is capable to any arbitrary degree of accuracy. This paper explains Noise-canceller in three major parts, concept, performance and comparison with standard multilayer perceptron neural networks. Simulation results and comparison with traditional MLP Networks have shown that this noise canceller offers better noise cancellation capability.

2. The architecture of noise-canceller

The neural network has already applied in signal processing particularly for signal detection applications [8] but this paper presents a simple and efficient GMN applied for noise canceller. The architecture of noise canceller is shown in the figure (1). In signal detection, useful signal is often corrupted by noise .The noisy signal is generated by addition of useful signal with White Gaussian noise signal. By delaying the measuring noisy signal the number of signal are generated to get the multiple inputs for the GMN.

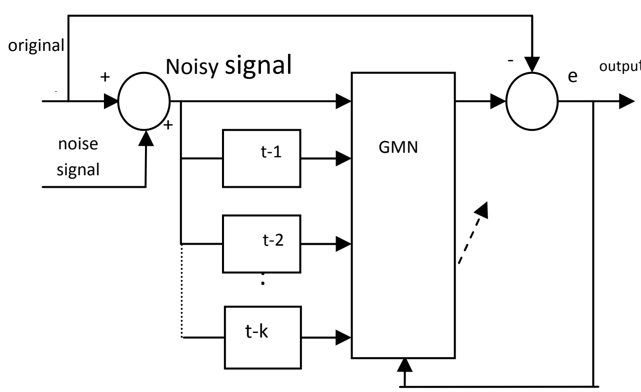

Fig-1 Architecture of noise-canceller

The Neural network is generalized - mean based neuron (GMN) model [2] has vast application prospects in signal processing. The GMN can approximate any non-linear function at any degree of accuracy. A well-defined training procedure based on standard back-propagation, the GMN considers a weighted generalized mean of all the inputs in the space. The aim of signal filtering is canceling noise to obtain useful signal. The output of GMN is the signal where the desired signal is subtracted from it to get the mean square error function and then tested till its zero value. The number of iterations results in detection of the useful signal by making error function to be remains constantly zero value and therefore the network produces the signal where noise is removed. The simplicity of the GMN, this method makes it convenient and efficient for the network to be used in different situations.

3. Generalized–mean neuron

Neuron modeling concerns with relating function to the structure of neuron is on the basis of its operation. The Higher-order neuron model is based on the concepts of **Generalized mean neuron model (GMN)** Figure-2. GMN has a multilayer feed forward network and error back propagation learning rule.
The detailed Neuron model and its learning algorithm can be seen in [2].

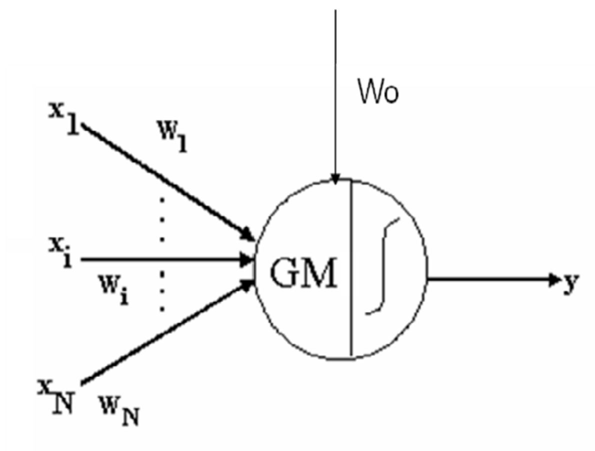

Fig.2 Generalized -mean neuron

As the name suggests the generalized mean neuron model is based on the concepts of generalized mean of the input signals. The generalized mean of N input signals
$x_j (j=1,2,3,\ldots N, N\in I)$ can be given as

$$GM = \frac{1}{N}\left[\sum_{j=1}^{N} x_j^r\right]^{1/r} \quad (1)$$

Where r ($r\in R$) is a generalization parameter, which gives various means (arithmetic mean, geometric mean and harmonic mean) depending upon its values. It also gives the max and min operators when the value of r is maximum ($+\infty$) and minimum ($-\infty$) respectively.

Aggregation function of the GMN can be defined as-

$$y(x_j w_j) = \left[\sum_{j=1}^{N} w_j x_j^r + w_o\right]^{1/r} \quad (2)$$

Where w_j is the adaptive parameter corresponding to each x_j and w_o is threshold of the neuron.

.4. Architecture of GMN network

GMN is a multilayer feed forward network where M hidden layer neurons receive N inputs as shown in the figure-3.The learning rate can be either be adapted with epic or can be fixed to a small number based on heuristics. This learning method is used for function approximation.

All multilayer networks reported are trained using the standard gradient descent-learning algorithm.

In the network

$n \times h_1 \times \ldots\ldots \times h_k \times o$

Where n- number of input nodes,

hi- number of nodes in the i^{th} hidden layer (for i= 1,…k),

o- number of output nodes

The input and output vectors of the network are

$X=[x_1,x_2,\ldots\ldots x_N]^T$

and $Y=[y_1,y_2,\ldots\ldots y_k]^T$ respectively.

If w_{ij} is a weight that connects the i^{th} neuron with j^{th} input, the activation value of the i^{th} neuron can be given as.

$$net_i = \left[\sum_{j=1}^{N} w_{ij} x_j^r + w_{oi} \right]^{1/r} \quad \text{for i = 1,2, .,M} \tag{3}$$

Where w_{oi} is bias of the i^{th} neuron in the hidden layer. The nonlinear transformation performed by each of M neurons in the network is given as

$$y_j = f(net_i) \quad \text{for i = 1,2, ...M} \tag{4}$$

Where f denotes a nonlinear function (sigmoid function in this case). Similarly output of the k^{th} neuron in the output layer can be given as

$$y_k = f(net_k) \quad \text{for k = 1,2,....K} \tag{5}$$

where

$$net_k = \left[\sum_{i=1}^{M} w_{ki} y_i^r + w_{ok} \right]^{1/r} \quad \text{for k=1,2...k} \tag{6}$$

Where w_{ki} is the weight that connects the i^{th} neuron of hidden layer to the k^{th} neuron of output layer and w_{ok} is bias to corresponding output layer neuron.

The value of the generalization parameter r, for simplicity, is considered same for every neuron in our simulations.

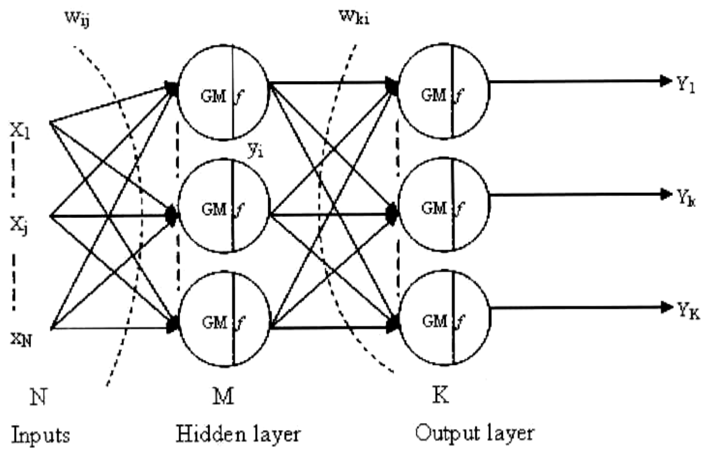

Fig. 3 Multilayer feed forward network using GMN Model

5. Results and discussion

To estimate and eliminate a noise component in some desired signal and system modeling an Adaptive filter is very popular and used as a model to detect the desired signal .One criterion that provides a good measure of performance in adaptive filtering applications is the Mean-square-error (MSE) criterion. In the proposed model adaptive filtering using new neural networks is one of the new and quite efficient methods of noise cancellation, which can be implemented easily against any of the models using a standard multilayer perceptron neural network. The comparison of this model with other existing model will be discussed in later section but first of all the performance of this Noise canceller using GMN is discussed here. The signals experimented for noise cancellation using GMN model are considered and generated just for convenience. The original useful signal is corrupted by White Gaussian noise of signal-to- noise ratio of 16dB. Corrupted signal is then delayed just to get a number of input signals $x_1(t)$, $x_2(t)$, $x_3(t)$. GMN takes generalized mean of all the noisy signals. Results of all the examples show the useful signals and noisy signals. In all simulations the results reported are average of 600 samples of 500 runs for a range of reported learning rates, and tested for value of r=0.9 in equation (2).

In all the examples the dataset has been processed by test and trial for better function approximation by changing the value of 'r' from 0.1 to 0.9. All multilayer networks reported are trained using standard gradient learning algorithm. We evaluate the capabilities of the proposed GMN and get the results shown in the fig-4,5,6, where the performance shows testing signals. In the performance graph of GMN the red line is the original signal and bold black dotted line is the detected output.

Example-1 is tested for the original signal considered from [1] just for convenience as
S1 (t) = 40/t

The white Gaussian noise of 16dB SNR is added to this signal to get noisy signal fig-4. To get the input signals for GMN the corrupted signals are delayed by (t-2), (t-5) and (t-7) just for convenience and then given to the GMN model. This model takes less time to train the neurons. The time taken in learning is 13.078 seconds when processed on core2 duo, 1.83GHz processor for experiment. The performance observed is at 500 iterations on average of 600 samples of dataset, the figure-4 shows the testing signal result.

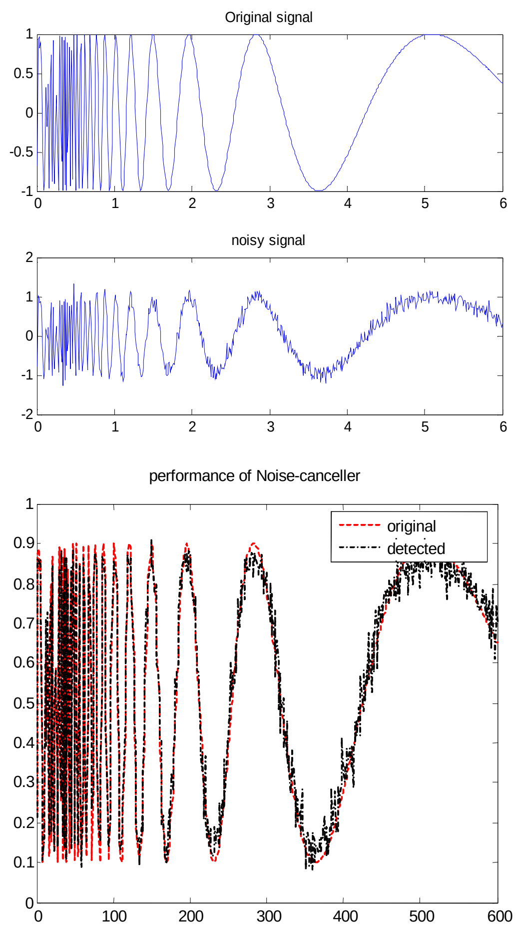

Fig.4 Performance of Noise-canceller sing GMN

Example-2 The signal generated is one kind of signal, which is a combination of sine and cosine, as usually found in the communication systems. It is considered just for experiment

S2 (t) = [sin (2π0.015(N-1))*0.5cos(2π 0.008(N-1)]

Where N can vary from 0 to N.
The results shown are at N=500,

Adding White Gaussian noise of SNR 16 dB corrupts this useful signal**.** Just by trial at r=0.9 the average of 1000 samples are considered in 500 runs and time taken for learning is 13.603 seconds, as shown in Figure-5

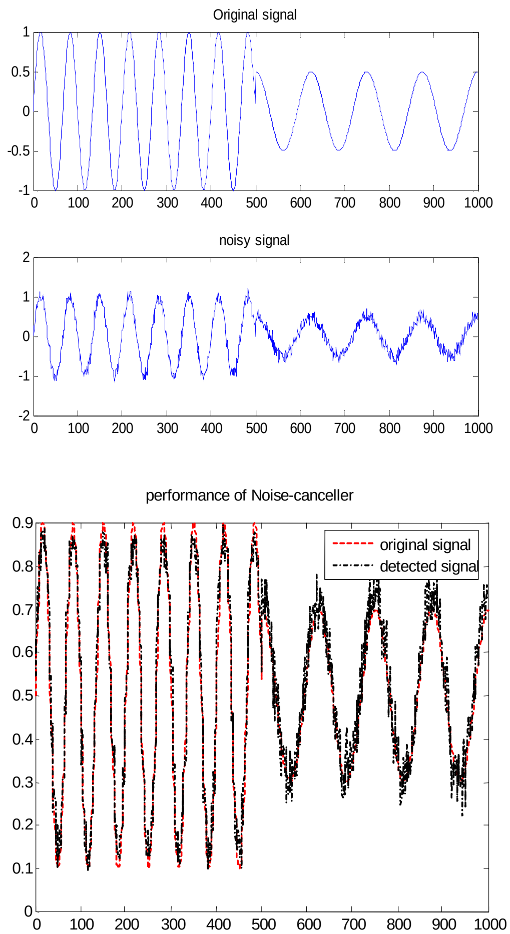

Fig-5 Performance of Noise-canceller using GMN

Example-3 The useful signal considered here is an application of adaptive filters in electrocardiography, in which any undesired heartbeat signal is adaptively removed from a useful ecg sensor signal.

S3(t) = Ecg signal

White Gaussian noise of 16 dB is added to useful signal to get noisy signal. Figure-6 shows original signal, noisy and detected signal. Simulation results reported are average of 600 samples of 1000 runs where learning time is 25.203 seconds. The numbers of iterations are considered here just by test and trial basis for better performance of noise canceller. The random nature of useful signal does not matter because once the neurons are trained the function approximation gives tested neurons accordingly.

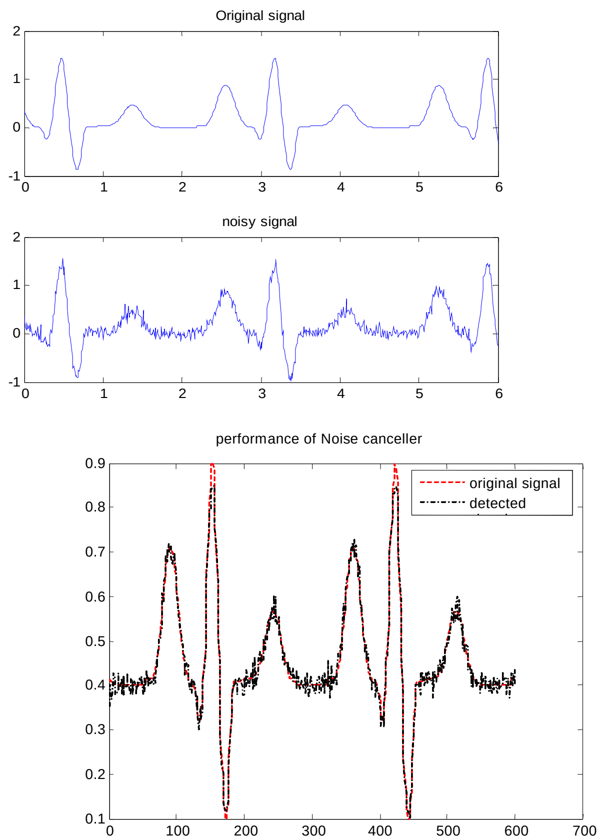

Fig-6 Performance of Noise-canceller using GMN

6. Performance analysis using GMN vs. MLP

The resulting neuron model has the same number of parameters with improved computational power as the existing multilayer perceptron (MLP) model [2]. Experimented results show the performance of both the models at different signal to noise ratio (SNR) and observed that the performance of GMN has better noise-cancellation

capability over a standard multilayer perceptron (MLP) neural network. The Error signal shows the Mean square error (MSE), which is the difference of useful and detected signal. All multilayer networks reported are trained using standard gradient learning algorithm. The learning curve shows the plot between Mean square error and Iterations for both the cases. Also the plot between MSE at different SNR in dB shows that GMN model achieves lower value of MSE in less iterations then MLP and it can be used at any arbitrary degree of accuracy. We evaluate the capabilities of the proposed GMN and MLP and get the parameters shown in the tables for different experimented signals. The tables give the comparative analysis of the parameters like MSE, Mean, Variance, and iterations for varying values of SNR.

The following experiment results and performances are analyzed for signals S1(t), S2(t), S3(t), considered in section 5- results and discussions. The values of MSE, Mean, and Variance at different SNR for three different experimental signals are given in the tables-1, 2 and 3.

Table-1 Parameter comparison at iteration = 500 for S1 (t).

SNR (dB)	GMN Networks			MLP Networks		
	MSE	Mean	Variance	MSE	Mean	Variance
0	0.0185	0.5495	0.0480	0.0185	0.5442	0.0506
4	0.0100	0.5586	0.0618	0.0100	0.5565	0.0637
8	0.0053	0.5567	0.0720	0.0052	0.5557	0.0738
12	0.0018	0.5649	0.0720	0.0020	0.5592	0.0761
16	5.7593e-004	0.5616	0.0724	9.3838e-004	0.5558	0.0775
20	2.0139e-004	0.5609	0.0728	5.3512e-004	0.5553	0.0778

Table-2 Parameter comparison at iteration =500 for S2(t).

SNR (dB)	GMN Networks			MLP Networks		
	MSE	Mean	Variance	MSE	Mean	Variance
0	0.0185	0.5495	0.0480	0.0185	0.5442	0.0506
4	0.0100	0.5586	0.0618	0.0100	0.5565	0.0637
8	0.0053	0.5567	0.0720	0.0052	0.5557	0.0738
12	0.0018	0.5649	0.0720	0.0020	0.5592	0.0761
16	5.7593e-004	0.5616	0.0724	9.3838e-004	0.5558	0.0775
20	2.0139e-004	0.5609	0.0728	5.3512e-004	0.5553	0.0778

Table-3 Parameter comparison at iteration =1000 (for S3 (t))

SNR(dB)	GMN Networks			MLP Networks		
	MSE	Mean	Variance	MSE	Mean	Variance
0	0.0047	0.4647	0.0074	0.0048	0.4598	0.0072
4	0.0026	0.4612	0.0115	0.0026	0.4572	0.0112
8	0.0013	0.4623	0.0135	0.0015	0.4574	0.0135
12	4.5872e-004	0.4570	0.0168	7.9624e-004	0.4527	0.0172
16	1.8005e-004	0.4662	0.0153	3.9868e-004	0.4639	0.0163
20	1.1372e-004	0.4630	0.0169	1.9801e-004	0.4625	0.0163

Example-1 The signal S1(t) is considered in noise canceller using both GMN and MLP networks and observed that GMN requires less number of iterations for achieving lowest value of mean square error. Learning curve for GMN and MLP is shown in figure-7. Using GMN at the 70 iterations, the value of MSE is 5.7593e-004 where as using MLP the value of MSE 9.3838e-004 is achieved in 90 iterations. For different values of SNR the variation of Mean-square error gives the performance measure for both the networks using GMN and MLP as shown in Figure-8.

This graph shows that for this particular signal, MSE gets its lower value earlier than MLP. At 8dB SNR the value of MSE for GMN is 0.0024 where as for MLP it is 0.004. Comparison of observed parameters is shown in the table-1.

Example-2 The signal S2(t) is tested for both the networks GMN and MLP and their comparative analysis for different parameters is shown in Table-2, For SNR=16 dB learning curve shows the MSE values at different iterations in figure-9. The performance of GMN noise canceller clearly shows here that in 80 iterations the MSE is 3.5467e-004 where as at the same value of SNR the value of MSE using MLP is 7.3827e-004 in 100 iterations. The training of neuron in GMN is faster than MLP. Comparison of MSE vs. SNR for both the cases is shown in the figure-10

Example-3 The ecg signal S3(t) is experimented for both the networks GMN and MLP and their comparative analysis for different parameters is shown in Table-3. Performance of GMN for this particular signal is good for at least 1000 Iterations, while in previous examples the iterations were 500. In the Fig 11 it is visible that the lower value of MSE is achieved by GMN in lesser number of iterations as compared to MLP. GMN gives 1.8005e-004 MSE in 230 iterations while MLP gives 3.9868e-004 MSE in 300 iterations. So learning time is lesser in GMN. All these simulations are at 16dB just considered on trial basis. For different value of SNR the change in MSE is shown in the figure-12. For this particular random ecg signal performance of GMN as compared to MLP is better even at 4dB of SNR, although for signals of other examples have similar performance observed for at least 8dB of SNR. And for 16 dB SNR the GMN has lowest value of its MSE is 1.8005e-004 and MLP achieves its lowest value of MSE i.e. 1.9801e-004 at 20dB of SNR. Thus Noise-canceller using GMN performs faster and more efficient for non-linear signal detection.

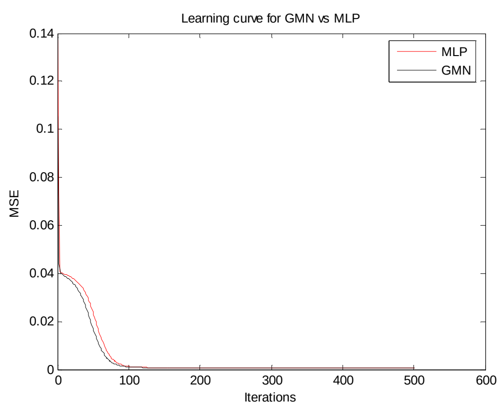

Fig-7 Learning curve for GMN and MLP (for s1(t))

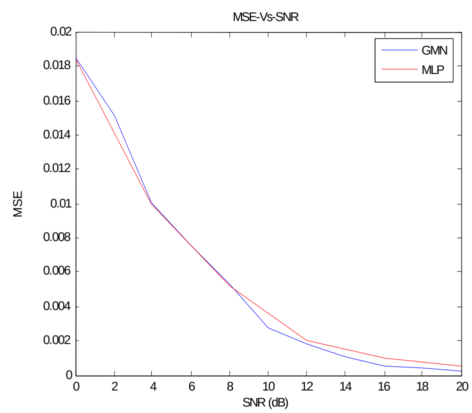

Fig-8 Performance analysis GMN vs. MLP (for S1 (t))

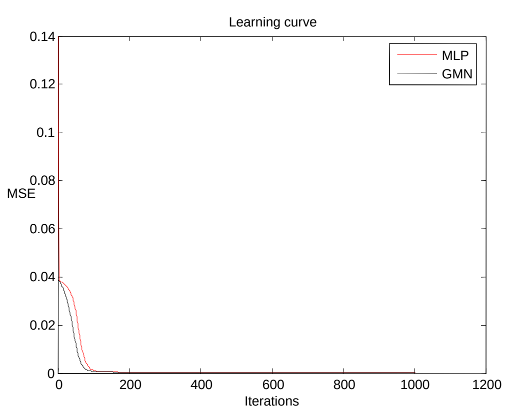

Fig -9 Learning curves for GMN and MLP (for S2(t))

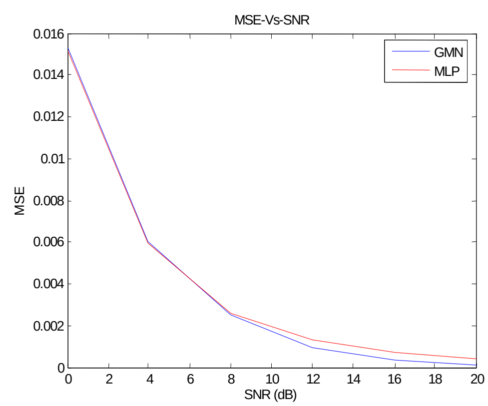

Fig-10 Performance analysis GMN vs. MLP (for S2 (t))

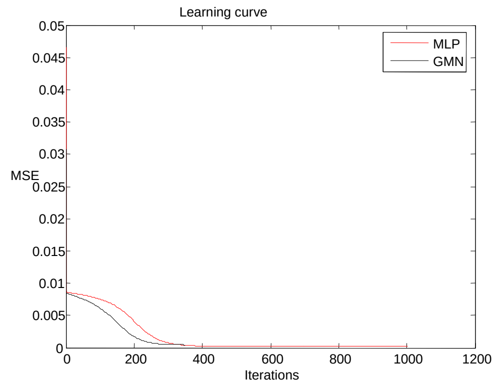

Fig 11 Learning curves for GMN and MLP (for S3 (t))

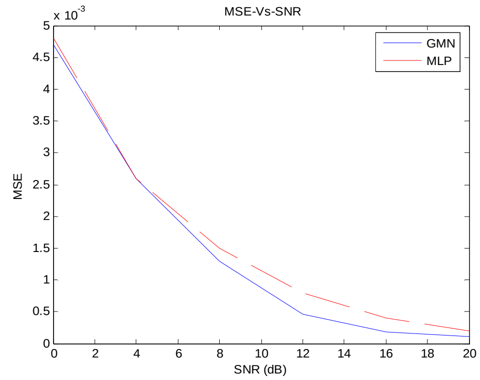

Fig-12 Performance analysis GMN vs. MLP (for S3 (t))

7. Conclusion

It concludes that a Noise-canceller based on GMN Network can be used significantly in the field of signal processing. This new approach performs fast and efficient for non-linear signal analysis. The comparison with standard Multilayer perceptron (MLP) Networks the parameters MSE, Mean, Variance for different signal to noise ratio show that GMN Neural network has very good capability of noise cancellation. The simulation results show the Noise-canceller using GMN networks can be suitably applied for the signal detection in adaptive filtering. The simplicity of GMN makes it convenient and efficient for the network to be used in different situations. Definitely this noise-canceller offers a new approach for signal detection in the series of application of Neural Networks in Adaptive filtering.

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