ADVANCES in NATURAL and APPLIED SCIENCES

ISSN: 1995-0772
EISSN: 1998-1090
2016 April 10(4): pages 500-507

Published BY **AENSI Publication**
http://www.aensiweb.com/ANAS
Open Access Journal

Application of Hybrid Wavelet Neural Network in One-Dimensional Signal Denoising using Multiple Wavelet Functions

[1]Jasmineet Kaur Arora, [2]Dr. Somanchi K. Murthy, [3]Dr. R.S. Deodhar (Sc.'F')

[1,2]Department of Applied Mathematics, DIAT, Girinagar, Maharashtra, India.
[3]Pinaka, ARDE, Pune, Maharashtra, India.

Received February 2016; Accepted 18 April 2016; Available 25 April 2016

Address For Correspondence:
Jasmineet Kaur Arora, Department of Applied Mathematics, DIAT, Girinagar, Maharashtra, India,
E-mail: jasmineetarora@gmail.com

Copyright © 2016 by authors and American-Eurasian Network for Scientific Information (AENSI Publication).
This work is licensed under the Creative Commons Attribution International License (CC BY).
http://creativecommons.org/licenses/by/4.0/

Open Access

ABSTRACT

Signal processing of one dimensional signal such as telemetric signals is a subject of intense research due to its strategic importance in various communication applications. A novel methodology for non-linear noise reduction based on wavelet transform theory is proposed, viz. Wavelet Neural Network (WNN) which provides a better alternative approach as opposed to conventional feed-forward neural network. Telemetric signals are contaminated with several electrical and mechanical noise components; as well as noises from the environment making it difficult to extract key features. A WNN possesses the characteristics of good localization from the wavelet transform theory and adaptive learning from neural networks, making it a useful tool for denoising. Back propagation algorithm is used for the said WNN for training; testing is performed with different types of wavelet functions and experimental results are reported.

KEYWORDS: Back propagation algorithm, Neural network, Non-linear noise reduction, Wavelet Neural Network (WNN), Wavelet transform.

INTRODUCTION

Artificial Neural Networks (NN) are capable of learning complicated functions, can generalize results for untrained inputs and have an ability to approximate to arbitrary specified accuracy given sufficient number of neurons. Hence over a period of time, NNs have been established as a general non-linear fitting tool to develop models by observation of time series or for learning mapping between input and output spaces [1]. The multi-layer perceptron (MLP) [2], trained using the back-propagation (BP) training algorithm, is probably the most frequently used type of neural network in practical applications [3]. Although wavelet transform has varied applications, there is a growing interest in using wavelet networks for non-linear regression. Many researchers have proven the ability of non-linear approximation using wavelets and neural networks [4]. Wavelet networks are being used both for static modeling and for dynamic input-output modeling. Recently, a variety of wavelet neural networks (WNN) have been proposed by combining the localization ability of wavelet transformation to reveal the properties of function with the learning ability and general approximation properties of neural networks. Boubez and Peskin [5], used orthonormal set of wavelet functions as basis functions. Yamakawa [6] and Wang [7,8] applied non-orthogonal wavelet function as an activation function in the single layer feed-forward neural network using a simple cosine wavelet activation function. Neural networks (NN) with sigmoidal activation function have shown the ability to compute large dimensional problems positively [9]. WNNs assist a

To Cite This Article: Jasmineet Kaur Arora,. Somanchi K. Murthy, Dr. R.S. Deodhar (Sc.'F')., Application of Hybrid Wavelet Neural Network in One-Dimensional Signal Denoising using Multiple Wavelet Functions. **Advances in Natural and Applied Sciences**. 10(4); Pages: 500-507

better system modeling application for complex and seismic applications as compared to the NN with sigmoidal activation function. Major applications of wavelets have been limited to small dimension [10], though WNN have the ability to handle large dimension problem [9]. In this paper a simple wavelet neural network (WNN) is proposed in which we use wavelet coefficients of the signal as an input to the neural network. The literature survey describes the efficacy of wavelets when used in wavelet network. But the problem of a comparative study of different types of the wavelets has not been catered to. In this work, we attempt to bring about comparative study for three types of wavelet functions used in WNN viz., Haar, Daubechies and Symlets. The underlying idea for this work is to combine the approximation of a non-stationary telemetric signal by using wavelet transform and then to use hyperbolic activation function in neural networks. The thought behind proposing the said WNN is to integrate the localization property of wavelets with functional approximation properties of neural network. The sharp temporal changes in the dynamic signals can be accumulated in wavelets. The output of every neuron is the summation of wavelet coefficients and the neural network training is performed such a way that the inverse wavelet transform is computed by the neural network itself. Ability of proposed model is examined using a single telemetric signal with different number of iterations and varying the number of nodes in the hidden layer. The rest of the paper is organized as follows: Section II proposes the WNN model. Section III describes Noise Reduction Structure. Simulation Results are revealed in Section IV, Section V is dedicated to discussion of results and Conclusions are relegated to Section VI.

II. Wavelet Neural Network Model:

The Wavelet Neural Network (WNN) belongs to the novel class of neural networks with special capabilities in a nonlinear time series analysis. Wavelets form a class of basis functions with finite-duration oscillations making them look like "little waves". Due to multi-resolution property of wavelets, they are ideal for analysis of physical signals. ANNs belong to a powerful class of nonlinear function approximates for model-free estimation. The concept of Wavelet Neural Network was inspired by both the technologies of wavelet decomposition and neural networks. The nonlinearity is approximated by superposition of sigmoid functions in standard neural networks, whereas in wavelet transform, superposition of a series of wavelet functions is used to approximate the nonlinearities. Due to this similarity between the two, combining Wavelet and Neural Network is an attractive idea. Fig.1 displays the overall scheme for noise reduction training and filter structure. The noisy signal is decomposed by Discrete Wavelet Transform (DWT) into wavelet and scaling coefficients. Sub-band coefficient thresholding is then perform on these coefficients filtering only those that represent signals of interest and discard coefficients that do not represent the signal in anyway. More detail about the thresholding scheme is explained in the next section. After the thresholding process, the remaining coefficients are those that truly represent and partially represent the given signal. Because noises among the coefficients still exist, a neural network is the last and final filtration process to remove the remaining noises mixture among the coefficients. In addition, neural network also computes Inverse Discrete Wavelet Transform (IDWT) on the signal, thus, rendering the final filtered signal. Note that normalization equation (2.1) and de-normalization equation (2.2) with [-1, +1] limited interval are placed as pre and post-processing units for the given signal.

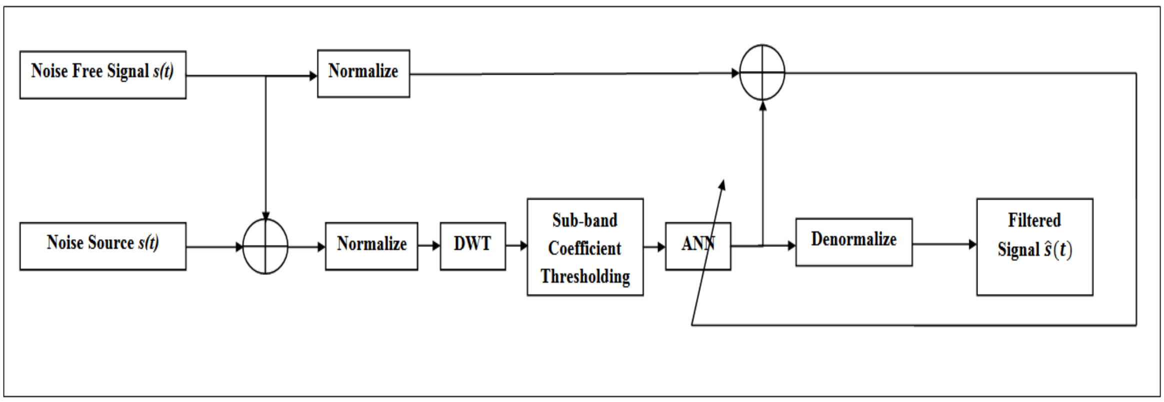


Fig. 1: Overall adaptive noise reduction training scheme

$$\hat{s}(t) = 2\left(\frac{s(t)-\min(X,Y)}{\max(X,Y)-\min(X,Y)}\right) - 1 \qquad (1)$$

$$s(t) = \frac{(\hat{s}(t)+1)(\max(X,Y)-\min(X,Y))}{2} + \min(X,Y) \qquad (2)$$

where s(t) and $\hat{s}(t)$ are signals of interest and its normalized form, respectively. Variables X and Y are the complete training sets for the input signal and reference signal. This step is performed because the activation function of NN is chosen to be hyperbolic. Because of its characteristic, all signals must be normalized down to the [-1, +1] range to accommodate for the activation function. The proposed NN is a simple multi-layer feed-forward structure

III. Noise reduction structure:

3.1. Noise reduction via wavelet decomposition and neural network:

A comparative study of three different classes of NNs has been made in this paper viz., $N_{32,20,12,10}$, $N_{32,30,20,10}$ and $N_{64,56,12,10}$. These sizes have been chosen after numerous simulations using the given signal. The number of input nodes is restricted to 32 and 64 resulting from DWT. This restriction will be explained clearly in next section. The number of nodes for hidden layers and output layer are chosen based on experiments. Though the number of output nodes is 10, it does not mean that the network maps its output 10 samples at the time of actual test run. As a matter of fact, only one of those outputs is taken into consideration. The remaining outputs act as extra references for comparison to generate more errors which are utilized by the back-propagation algorithm to update the weights for the hidden layers thereby improving the efficiency of the learning process. After completion of training, 9 out of the 10 outputs will be discarded.

3.2. Discrete Wavelet Transform and Coefficient thresholding:

The signal is normalized and a window size of 256, 256 and 512 samples is chosen for $N_{32,20,12,10}$, $N_{32,30,20,10}$ and $N_{64,56,12,10}$ respectively to find DWT of the signal. This number has been selected based on the restriction of length of wavelet input which must be divisible by 2^L where L is number of decomposing level. After the DWT coefficients are obtained, thresholding is done to remove any irrelevant coefficients. The remaining coefficients are processed using NN. Thresholding can be performed in several ways such as soft thresholding and hard thresholding. However, for denoising method presented in this paper, the unwanted coefficients are simply discarded i.e. removed from the simulation process. Sub-band coefficient thresholding serves two main purposes: first to remove unwanted frequency-noise bands which are mostly white noise and secondly, helping in reduction in the number of input nodes for NN. As a result, less unnecessary information is presented to the NN for processing. Hence, the number of hidden nodes is reduced leading to a decrease in the amount of time needed for training. The DWT process separates signal into different frequency bands, using series of low-pass and high-pass filters. In case of this paper, the signal is sampled at 1 kHz, the first level of DWT will separate signal into 0-500Hz and 500-1000Hz roughly. At the second stage, the lower half is further split into 0-250Hz and 250-500Hz. In the third stage we have a further splitting of lower half frequencies into 0-125Hz and 125-250Hz. We are interested in the 0-100Hz frequency range for noise reduction of the signal. Therefore, out of the chosen 256 and 512 sample points that are transformed through DWT, only 32 and 64 coefficients respectively, are presented to the NN. Since we are interested in 0-100Hz frequency range, anything higher that 125 Hz can simply be considered as noise and can be discarded. This eliminates unwanted noise and also reduces number of input nodes of the NN. The signal used for training is in the first 1280 samples from a source with noise added to it, followed by a noisy signal of 1280 samples which is used for testing. The same signal is used for all the three types of NN architecture and for each of these architectures, the three wavelets viz., Haar, Daubechies (order4) and Symlet (order4) are implemented with different number of iterations (400,800,1200 and 1600 respectively). For each of these cases signal to noise ratio of the test signal is computed.

$$SNR_{dB} = 20log_{10}\left(\frac{A_{signal}}{A_{noise}}\right) \quad (3)$$

Where SNR_{dB} stands for Signal-to-noise ratio in decibels, A_{signal} is root mean squared value of amplitude of signal and A_{noise} is root mean squared value of amplitude of noise.

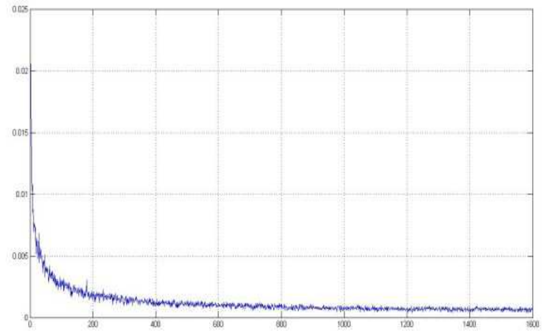
IV. Simulation results:

The effectiveness of the proposed method is demonstrated by experimental runs providing a comparative study of alternative selections of network models and wavelets.

Table 1: SNR values for $N_{32,20,12,10}$

	Types of Wavelets		
No. of Iterations	Haar	Daubechies (order 4)	Symlet (order 4)
400	30.0832647177817	28.7179055550779	28.5161977153336
800		30.1285066409101	29.6309878505537
1200	30.2369312227741	30.3103710677221	30.9585796089385
1600	31.5747719439454	29.690961968725	31.9615879410286

Following graphs show the error versus number of iterations and graph of test signal when applied to WNN for different wavelets and fixed number of iterations=1600



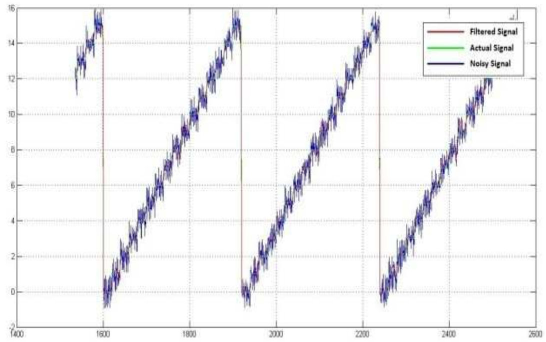
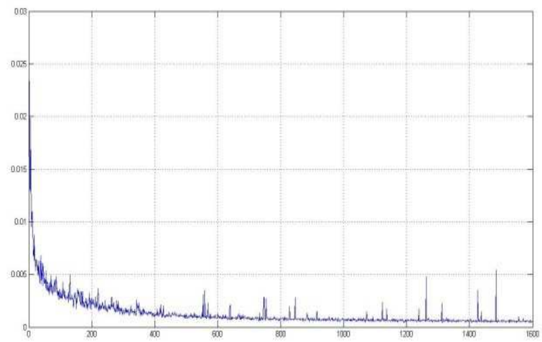


Fig. 2.a1: Error vs No. of Iterations

Fig. 2.a2: Amplitude vs Time

Figures 2.a(1) and 2.a(2) are outputs using Haar wavelet



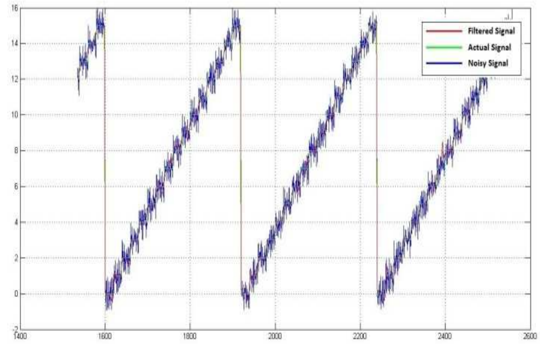
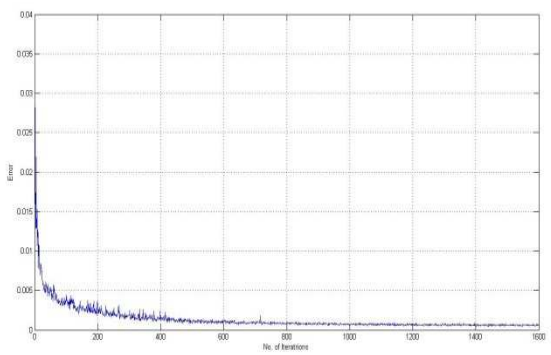


Fig. 2.b1: Error vs No. of Iterations

Fig. 2.b2: Amplitude vs Time

Figures 2.b(1) and 2.b(2) are outputs using Daubechies (order 4) wavelet



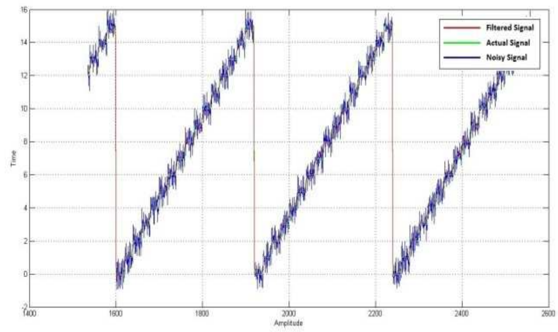


Fig. 3.c1: Error vs No. of Iterations

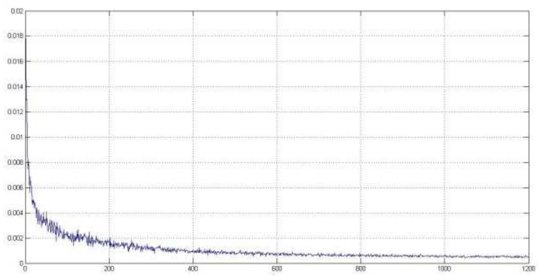
Fig. 2.c2: Amplitude vs Time

Figures 2.c(1) and 2.c(2) are outputs using Symlet (order4) wavelet

Table 2: SNR_{dB} values for $N_{32,30,20,10}$

	Types of Wavelets		
No. of Iterations	Haar	Daubechies (order 4)	Symlet (order 4)
400	29.2753876512657	29.5903151135754	28.2516506427013
800	31.0583687919813	29.4508485796359	29.4525167471447
1200	32.413127268779	29.1411183380645	30.3835935857994
1600	31.4610191789781	30.5574737582817	29.1904624122982

Following graphs show the error versus number of iterations and graph of test signal when applied to WNN for different wavelets and fixed number of iterations=1200



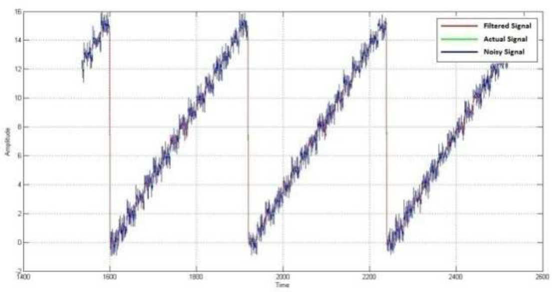
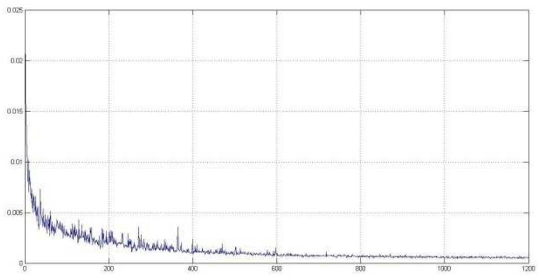


Fig. 3.a1: Error vs No. of Iterations **Fig. 3.a2:** Amplitude vs Time

Figures 3.a(1) and 3.a(2) are outputs using Haar wavelet



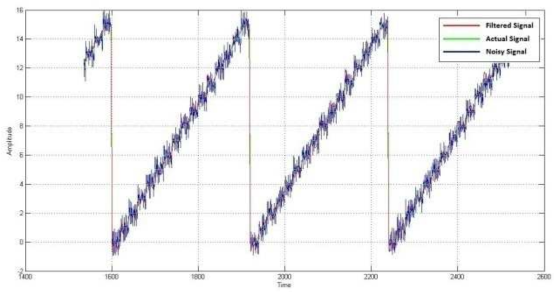
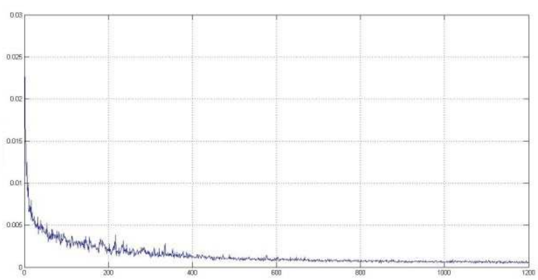


Fig. 3.b1: Error vs No. of Iterations **Fig. 3.b2:** Amplitude vs Time

Figures 3.b(1) and 3.b(2) are outputs using Daubechies (order 4) wavelet



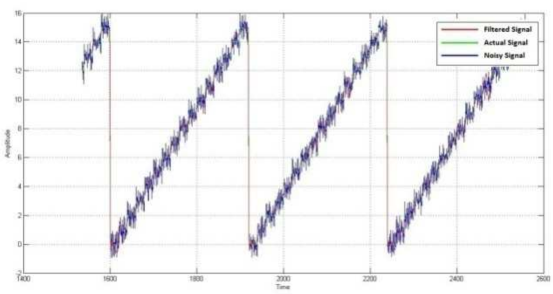


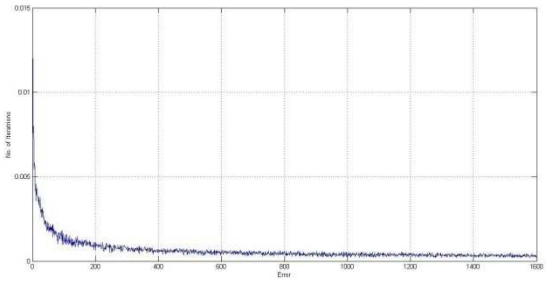
Fig. 3.c1: Error vs No. of Iterations **Fig. 3.c2:** Amplitude vs Time

Figures 3.c(1) and 3.c(2) are outputs using Symlet (order4) wavelet

Table 3: SNR_{dB} values for $N_{64,56,12,10}$

	Types of Wavelets		
No. of Iterations	Haar	Daubechies (order 4)	Symlet (order 4)
400	28.5759613457344	30.9678950760512	30.0351795629633
800	30.756210971993	29.9913236464326	31.4830658826225
1200	32.0592454332675	29.779234184112	29.9464328552786
1600	32.5400919395895	30.756210971993	29.3472138923107

Following graphs show the error versus number of iterations and graph of test signal when applied to WNN for different wavelets and fixed number of iterations=1600



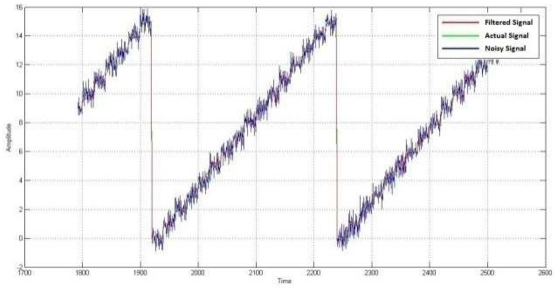
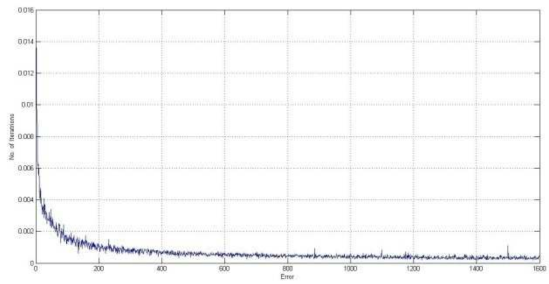


Fig. 4.a1: Error vs No. of Iterations **Fig. 4.a2:** Amplitude vs Time

Figures 4.a(1) and 4.a(2) are outputs using Haar wavelet



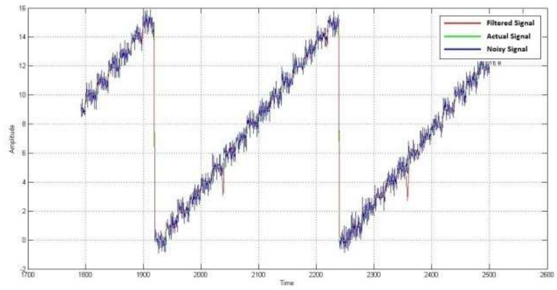
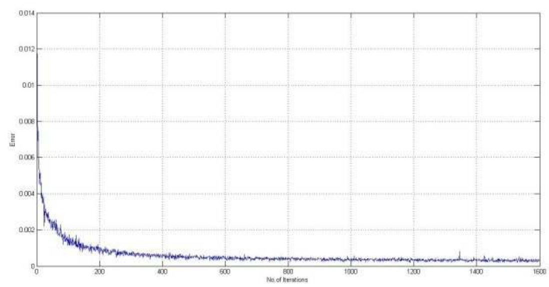


Fig. 4.b1: Error vs No. of Iterations **Fig. 4.b2:** Amplitude vs Time

Figures 4.b(1) and 4.b(2) are outputs using Daubechies (order 4) wavelet



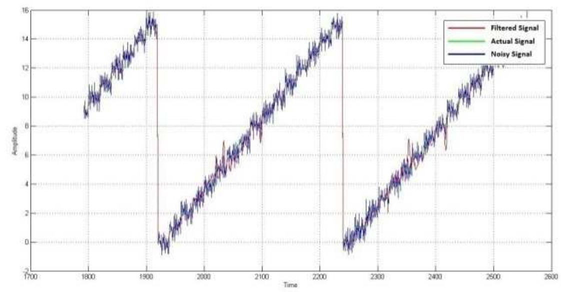


Fig. 4.c1: Error vs No. of Iterations **Fig. 4.c2:** Amplitude vs Time

Figures 4.c(1) and 4.c(2) are outputs using Symlet (order4) wavelet

Discussion:

From the consolidated tables, we can observe that for the given type of signal, processing using Haar wavelet yields better results than Daubechies 4 or Symlets 4. Symlets 4 give a higher SNR as compared to Daubechies 4.

From Table 1, we can observe that using 1600 iterations yields best results for $N_{32,20,12,10}$ type of architecture. For $N_{32,30,20,10}$ type of architecture, Table 2 shows the minimum error saturates at 1200 iterations and the best value of SNR is obtained at 1200 iterations. We can observe that 1600 iterations are needed for saturation of error for $N_{64,56,12,10}$ structure from Table 3 and we get the best result for SNR for 1600 iterations.

Conclusion:

Since the telemetry signal is considered to be contaminated by random, white-Gaussian noise, the DWT plays a significant role in improving the SNR by eliminating the coefficients corresponding to higher frequencies which in fact represent the components coming from noise. Also, this removes the unwanted coefficients thereby reducing the number of inputs that need to be processed by the NN and improves efficiency of NN by making the inputs more organized. This helps the NN to determine the relationship between in Input and Output more easily. The method of wavelet decomposition and NN presented in this paper has demonstrated its noise reduction capability of highly non-linear and non-stationary signals through an application of telemetric signal. The filtered signals have shown a good SNR improvement over the contaminated signals. This method is superior as compared to conventional methods as it does not depend on the details of the signals studied. The NN can learn from sample data during training and adapt to the basic shape of the signal to reproduce the signal again during operation. Adaptability of NN gives it the capability to learn but also leads to inconsistency during training which means that if two identical data sets are given to same NN, but trained at different times, will yield different results. It is difficult to predict the best asymptotic results and even if additional resources are added the computational time may become prohibitive. Good training data set also influences the improvement in results. In this paper, we have proposed a novel dynamic non-linear wavelet domain coefficient thresholding model and multi-layer NN for telemetric signals. Experimental results show that the method is able to achieve good SNR. The proposed model has prospective applications in other fields as well.

ACKNOWLEDGEMENTS

We would like to thank Dr. R.N.Pralhad (Sc. ‘F’) for his continuous guidance in completion of this work. We are also grateful to Shri. P.L.Bora (Sc. ‘F’, DOI, DRDL) and Shri Ashish Kumar Nanda (Sc. ‘D’, DOI, DRDL) for encouraging us to pursue a study in this field.

REFERENCES

1. Kai, C. and Y. Hamamatsu, 2004. An adaptive hybrid wavelet neural network and its application. In Robotics and Biomimetics, 2004. ROBIO 2004. IEEE International Conference on, pp: 779-784.
2. Rumelhart, D.E., G.E. Hinton and R.J. Williams, 1985. Learning internal representations by error propagation (No. ICS-8506). CALIFORNIA UNIV SAN DIEGO LA JOLLA INST FOR COGNITIVE SCIENCE.
3. Zhang, J., G.G. Walter, Y. Miao and W.N.W. Lee, 1995. Wavelet neural networks for function learning. Signal Processing, IEEE Transactions on, 43(6): 1485-1497.
4. Banakar, A. and M.F. Azeem, 2006. A New Artificial Neural Network and its Application in Wavelet Neural Network and Wavelet Neuro-Fuzzy Case study: Time Series Prediction. In 2006 3rd International IEEE Conference Intelligent Systems.
5. Boubez, T.I and R.L. Peskin, 1993. Wavelet neural networks and receptive field partitioning. In Neural Networks, 1993., IEEE International Conference on, pp: 1544-1549.
6. Yamakawa, T., E. Uchino and T. Samatsu, 1994. Wavelet neural networks employing over-complete number of compactly supported non-orthogonal wavelets and their applications. In Neural Networks, 1994. IEEE World Congress on Computational Intelligence., 1994 IEEE International Conference on, 3: 1391-1396.
7. Ting, W. and Y. Sugai, 1999. A wavelet neural network for the approximation of nonlinear multivariable function. In Systems, Man, and Cybernetics, 1999. IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on, 3: 378-383.
8. Ting, W. and Y. Sugai, 1999. A wavelet neural network for the approximation of nonlinear multivariable function. In Systems, Man, and Cybernetics, 1999. IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on, 3: 378-383.
9. Zhang, Q., 1994. Using wavelet network in nonparametric estimation.

10. Benveniste, A., A. Juditsky, B. Delyon, Q. Zhang and P.Y. Glorennec, 1996. Wavelets in identification. NATO ASI SERIES F COMPUTER AND SYSTEMS SCIENCES, 153: 435-478.