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Comparative Analysis of Different Wavelet Functions using Modified Adaptive Filtering Based on Wavelet Transform

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ABSTRACT
The traditional method of wavelet denoising is inefficient in removing the overlap noise between noisy signal and noise, due to which a modified adaptive filtering based on wavelet transform method is introduced. The method used in this paper filters out the noise on the basis of wavelet denoising using different wavelet functions. The simulation results indicate the Signal to Noise ratio (SNR), Mean Square Error (MSE) and signal error power spectral density comparison plot between different wavelet functions. These comparison results verified that Daubechies is more efficient than other wavelet functions in filtering out noise in all perspectives.
Keywords:- Adaptive Filtering, Denoising, Wavelet function, Wavelet transform, Weight

I. INTRODUCTION

Nowadays signal processing technology plays a vital role in communication, radar, sonar, biomedical and various other fields. Adaptive filter is a signal processing method that can automatically adjust the iterative filter parameters when the statistical properties of input signal are unknown [1]. Wavelet transform has the robust ability to approximate functions that are nonlinear or contain sharp discontinuities [2]. In adaptive filter model, the noise component is decomposed by wavelet transform and then used as the adaptive filter input and after iterations, signal-noise separation results with a very high performance can be achieved. The wavelet can make the information matrix of adaptive algorithm more diagonal and its convergence rate is also fast [3]. Discrete wavelet transform is effective not only for stationary noise but also for non-stationary noise, also it has a reduced complexity and better convergence rate than traditional algorithms [4]. Wavelet transform analyze the speech signals by varying window length, hence, it is useful for analyzing non-stationary signals. For non-stationary signals the components decoupling process is more complicated due to phase shifting during filtration process [5].

II. THEORY

1. Discrete Wavelet Transform (DWT)

Discrete wavelet transform is a wavelet transform in which wavelets are discretely sampled. This transform disintegrates the signal into mutually orthogonal set of wavelets. For given displacement *t*, wavelet function $\psi(t)$ and signal $x(t)$ can be described as follows:

$$WT_f(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\, \psi^*\left(\frac{t-\tau}{a}\right) dt, a > 0 \quad (1)$$

where a, τ are the parameters of wavelet function.

The parameters a and τ in the basic wavelet function $\psi a,\tau(t) = \frac{1}{\sqrt{a}}\left(\frac{t-\tau}{a}\right)$ are not allowed at various discrete points. This is done in order to reduce the repeatability of wavelet transform coefficients. In order to remove these type of obstacles discrete wavelet transform can be defined as:

$$WT_f\left(a_0^j, k\tau_0\right) = \int f(t)\psi^*_{a_0^j,k\tau_0}(t)\, dt \quad (2)$$

where $j = 0,1, \dots k\epsilon Z$

The decomposition of the original signal can be done by DWT fast algorithm using mallat algorithm:

$$c_1(k) = \sum_{n=-\infty}^{\infty} c_0(n).h(n-2k) \quad (3)$$

$$d_1(k) = \sum_{n=-\infty}^{\infty} c_0(n).g(n-2k) \quad (4)$$

where

$$\text{h(n)} = \int_{-\infty}^{\infty} \varphi_{m+1,0}(t)\varphi_{m,n}(t)\, dt \quad (5)$$

$$\text{g(n)} = \int_{-\infty}^{\infty} \psi_{m+1,0}(t)\psi_{m,n}(t)dt \quad (6)$$

2. Wavelet Functions

Adaptive filtering based algorithms generally using orthogonal wavelet functions. The wavelet functions used in this proposed paper are as follows:

2.1 Haar

The Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies 1 (db1). It is simplest and has linear phase characteristics [6].

2.2. Daubechies

Daubechies wavelets are orthogonal wavelets defining discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function called father wavelet that generates an orthogonal multiresolution analysis. It has finite number of filter parameters and hence fast implementation. It has high compressibility and is very asymmetric [7].

2.3. Symlets

Symlet wavelets are modified version of Daubechies wavelets with increased symmetry. It exhibits both orthogonal and biorthogonal properties [7].

2.4 *Coiflets*

Coiflets are discrete wavelets designed by Ingrid Daubechies to have scaling functions with vanishing moments. It has highest number of vanishing moments for both phi and psi for a given support width [7].

3. Wavelet Denoising

In wavelet denoising, the first task is to disintegrate the wavelet into signal. Generally higher frequency detailed signal includes the noisy signal. Wavelet decomposition coefficients generally interact with threshold or other forms in order to remodel wavelet to signal at the end, for the sake of signal denoising.

III. ADAPTIVE FILTER ALGORITHM

1. Adaptive Filter

Adaptive filter is a self-adjusting digital filter that can minimize an error function by adjusting its coefficients. This error function is also known as cost function, is the difference between the desired signal and the filter output.

2. Algorithm

Least mean square (LMS) as well as its improved versions can be applied to adaptive filters. LMS algorithm relies on least mean square error. In this the square of the value of difference between ideal signal and filter output should be minimum and weights can be modified on the basis of these values. This algorithm is generally simple and easy to implement in real time system but its convergence rate is small in comparison to recursive least square (RLS) algorithm. RLS basically generates an autocorrelation matrix for recursive estimate update by using the inverse of the input signal. Its convergence rate is fast but calculations are highly complex and also it needs great amount of storage for real time realization.

The main significance is to choose an adaptive filter that is fast, having high convergence rate and of good numerical stability.

IV. OPERATION

A modified adaptive filter model based on wavelet transform is generated by taking the signal after the first wavelet threshold denoising as the main input of the adaptive filter and then taking the wavelet reconstruction coefficients as the reference input of the adaptive filter after the second wavelet transform.

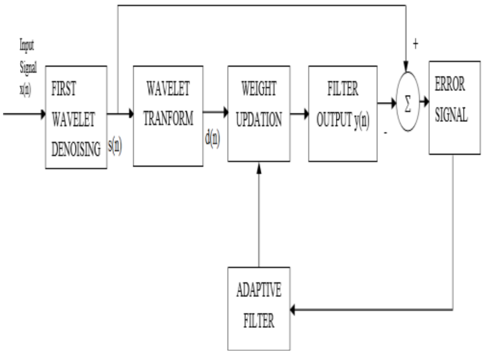

Fig. 1 Block diagram of the proposed model

Firstly, the input signal x(n) is applied to the first wavelet denoising and the signal s(n) which is contaminated with a small amount of noise, is obtained. Then the second wavelet transform is applied to s(n) and noisy signal d(n) is reconstructed, where s(n) is the overlap between the original signal and the noise with a small amount of spectrum overlay and it is used as the main input of adaptive filter and d(n) is used as the reference input of adaptive filter. Finally, error signal e(n), is obtained after calculating the difference between signal s(n) with filter output y(n) which is shown in Fig.1. in order to update or modify the weights. On the basis of this error signal, mean square error (MSE) has been calculated:

$$E\{e^2\} = E\{(s + n_0 - y)^2\} = E\{s^2\} + E\{n_0 - y)^2\} \quad (7)$$

The implementation of modified adaptive filtering based on wavelet transform basically relies on following iterative formulas:

$$y(k) = \sum_i^{M-1} w_i(k)x(k-i) \quad (8)$$

$$e(k) = d(k) - y(k) \quad (9)$$

$$w_i(k+1) = w_i(k) + 2\mu e(k)x(k-i) \quad (10)$$

Here *x(k)* is the input of the adaptive filter; *y(k)* is the output of the adaptive filter; *d(k)* is the reference signal; *e(k)* is the error; w_i is the filter weight coefficient; μ is the step; M is the filter order.

V. SIMULATION RESULTS

The experiment is simulated on the platform MATLAB 8.5.

1. First take original signal and then noisy signal bumps having signal to noise ratio 3 are added to it, which is shown in Fig. 2 and Fig. 3 respectively.

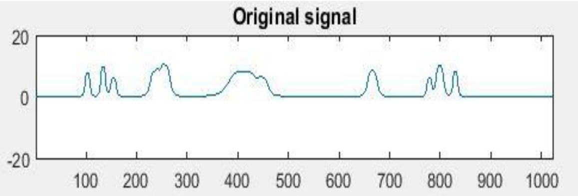

Fig. 2 Original Signal

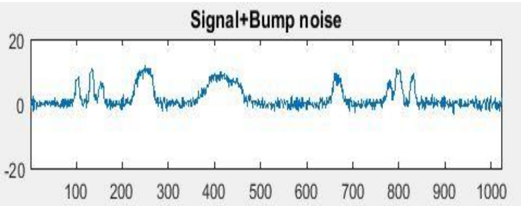

Fig. 3 The noisy signal bumps

2. Select the wavelet basis function and use appropriate soft threshold denoising method.
3. Take the signal after first denoising as the main input of the adaptive filter and then apply wavelet transform and take the coefficients after decomposition for reconstruction to be the adaptive filter reference input.
4. Select LMS algorithm for adaptive filtering with adaptive filter order 16 and step factor as 0.0001.
5. Result Analysis shows the comparison of the signal to noise ratio (SNR) between original denoising method and wavelet based adaptive filtering method for different wavelet functions. The results are shown in TABLE 1.

TABLE 1. Comparison of SNR for different wavelet functions

S. No.	Wavelet Functions	Original Denoising Method(SNR)	Wavelet based Adaptive Filtering Method (SNR)
1.	Daubechies	89.5168	91.0849
2.	Symlets	82.5244	87.0425
3.	Coiflets	68.9326	70.7043
4.	Haar	48.5784	49.4877

It is clearly depicted from the TABLE 1 that Daubechies wavelet function gave better results in comparison to other wavelet functions using wavelet based adaptive filtering.

The signal error power spectral density figures for both original denoising method and wavelet based adaptive filtering method using different wavelet functions are shown below:

5.1 Daubechies

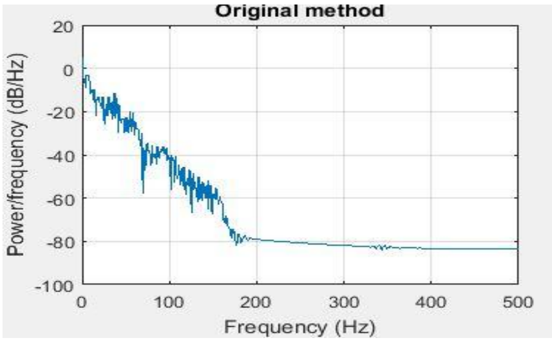

Fig. 4 Error power spectral plot for original denoising method

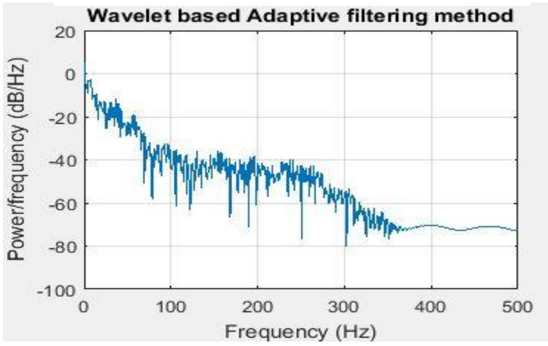

Fig. 5 Error power spectral plot for wavelet based adaptive filtering method

5.2 Symlets

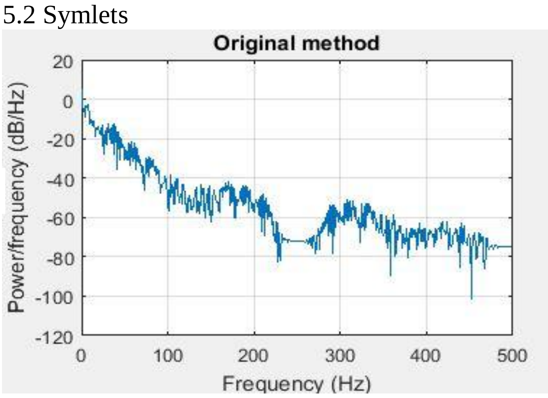

Fig. 6 Error power spectral plot for original denoising method

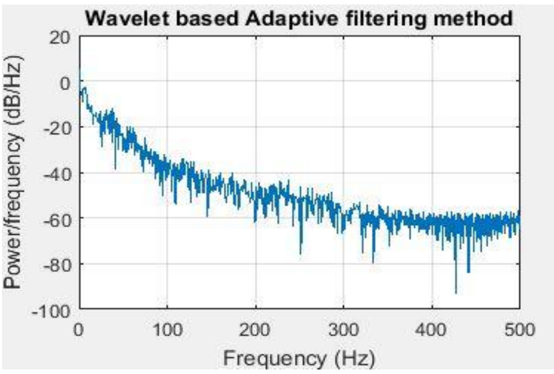

Fig. 7 Error power spectral plot for wavelet based adaptive filtering method

5.3 Coiflets

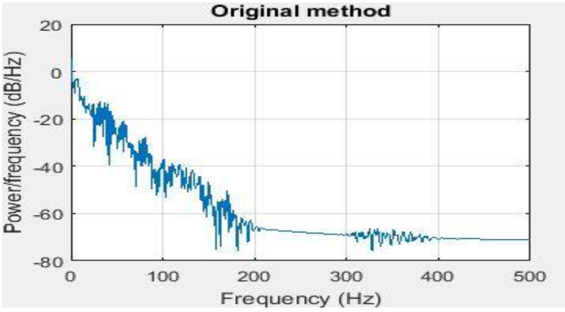

Fig. 8 Error power spectral plot for original denoising method

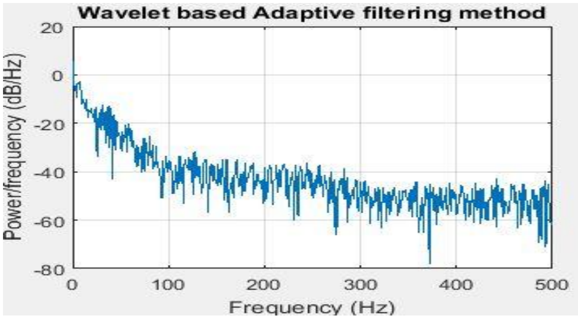

Fig. 9 Error power spectral plot for wavelet based adaptive filtering method

5.4 Haar

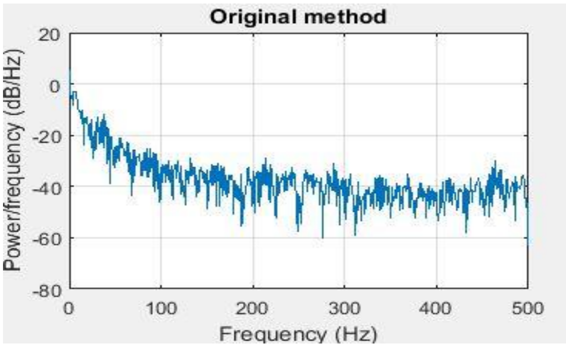

Fig. 10 Error power spectral plot for original denoising method

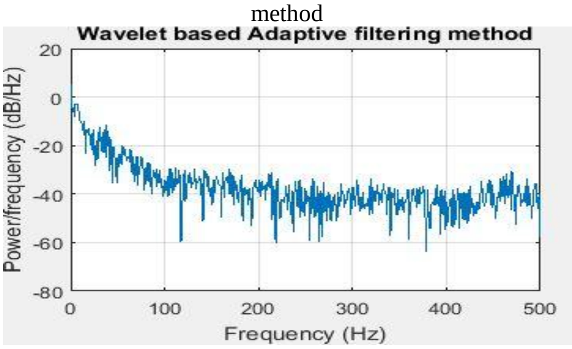

Fig. 11 Error power spectral plot for wavelet based adaptive filtering method

VI. CONCLUSION

In this paper, a modified adaptive filter model based on wavelet transform is structured. By using this model signal to noise ratio (SNR) of various wavelet functions is calculated and results are compared with one another in order to justify that which wavelet function is efficient among others.

VII. ACKNOWLEDGMENT

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