

Comparative Study of Vibration Signal Using Wavelet Transform

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ABSTRACT

Scientists have developed mathematical methods to imitate the processing performed by our body and extract the frequency information contained in a signal. These mathematical algorithms are called transforms and the most popular among them is the Fourier Transform. The method to analyze non-stationary signals is to first filter different frequency bands, cut these bands into slices in time, and then analyze them. The wavelet transform uses this approach. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle.

Keywords : Vibration Analysis, Spectral Analysis, Wavelet Transform Vibration Signal.

I. INTRODUCTION

To overcome the limitation of FT, Short Time Fourier Transform (STFT) was proposed. There is only a minor difference between STFT and FT. In STFT, the signal is divided into small segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window in time must be equal to the segment of the signal where it is still be considered stationary. By STFT, one can get time-frequency response of a signal simultaneously, which can't be obtained by FT. The short time Fourier transform for a real continuous signal is defined as:

$$X(f, t) = \int_{-\infty}^{\infty} [x(\tau)w(t - \tau)] e^{-j\omega\tau} d\tau$$

Where the length of the window is $(t-\tau)$ in time such that we can shift the window by changing value of t , and by varying the value τ we get different frequency response of the signal segments.

The basis set of wavelets is generated from the mother or basic wavelet is defined as:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right); a, b \in \mathfrak{R} \text{ and } a > 0 \text{ -- (1.1)}$$

The variable 'a' (inverse of frequency) reflects the scale (width) of a particular basis function such that its large value gives low frequencies and small value gives high frequencies. The variable 'b' specifies its translation along x-axis in time. The term $1/\sqrt{a}$ is used for normalization.

II. LITERATURE REVIEW

1-D Discrete wavelet transform

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discretise the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal / ortho normal set of basis wavelets.

$$\Psi_{m,n}(t) = 2^{m/2} \psi(2^m t - n); m, n \in Z \text{ such that } -\infty < m, n < \infty \text{ ----- (2.5)}$$

The 1-D DWT is given as the inner product of the signal $x(t)$ being transformed with each of the discrete basis functions.

III. THE SIMULATION METHOD

Five types of Wavelet Transform Implemented:

- 1) Haar Wt
- 2) Coiflet-5 Wt
- 3) Daubenchies
- 4) Bior
- 5) Symlet-5

In wavelet decomposing of an Signal, the decomposition is done row by row and then column by column. For instance, here is the procedure for an N x M image. You filter each row and then down-sample to obtain two N x (M/2) images. Then filter each column and subsample the filter output to obtain four (N/2) x (M/2) images.

A valid signal model is necessary for accurate Vibration detection. Normally, a vibration waveform is represented as a sinusoid and normal distribution white noise (Gaussian noise) as follows:

1 Haar wavelet

The Haar transform is based on the calculations of the averages (approximation co-efficient) and differences (detail co-efficient). Given two adjacent pixels a and b, the principle is to calculate the average $s = \frac{(a+b)}{2}$ and

the difference $d = a - b$. If a and b are similar, s will be similar to both and d will be small, i.e., require few bits to represent. This transform is reversible, since $a = s - \frac{d}{2}$ and $b = s + \frac{d}{2}$ and it can be written using matrix notation as

$$(s, d) = (a, b) \begin{pmatrix} 1/2 & -1 \\ 1/2 & 1 \end{pmatrix} = (a, b)A,$$

$$(a, b) = (s, d) \begin{pmatrix} 1 & 1 \\ -1/2 & 1/2 \end{pmatrix} = (s, d)A^{-1}$$

In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis.

IV. EXPERIMENT RESULT

Tool Used for analysis is Matlab 8.3

Simulation of the proposed system has been done in Matlab software. Simulation results are shown in fig

Analysis by haar wavelet

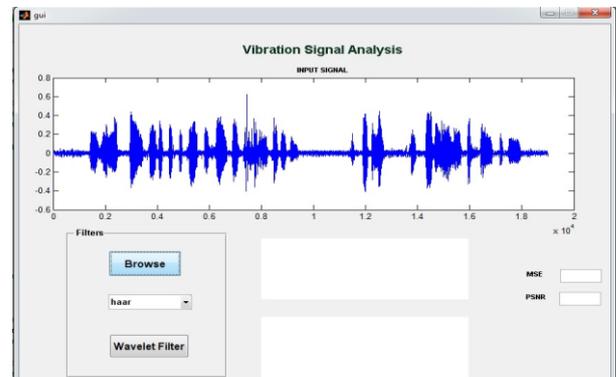


Figure 1. Input Vibration signal

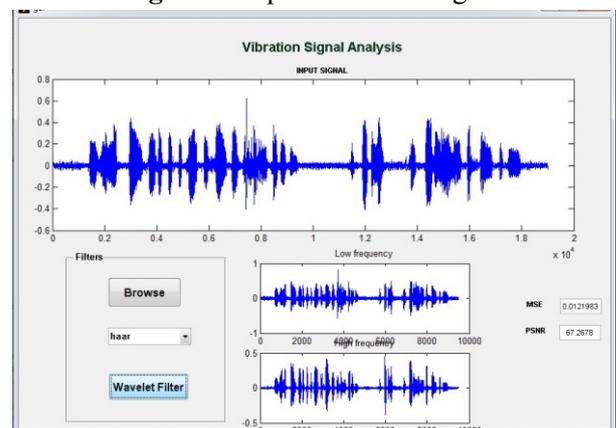


Figure 2. Output of haar WT

1. Analysis by Coiflet wavelet:

Coiflets are discrete wavelets designed by Ingrid Daubechies, at the request of Ronald Coifman, to have scaling functions with vanishing moments. The wavelet is near symmetric, their wavelet functions have $N/3$ vanishing moments and scaling functions $N/3 - 1$, and has been used in many applications using Calderón-Zygmund Operators

2. Coiflet Coefficients

Both the scaling function (low-pass filter) and the wavelet function (High-Pass Filter) must be normalised by a factor $1/\sqrt{2}$. Below are the coefficients for the scaling functions for C6-30. The wavelet coefficients are derived by reversing the order of the scaling function coefficients

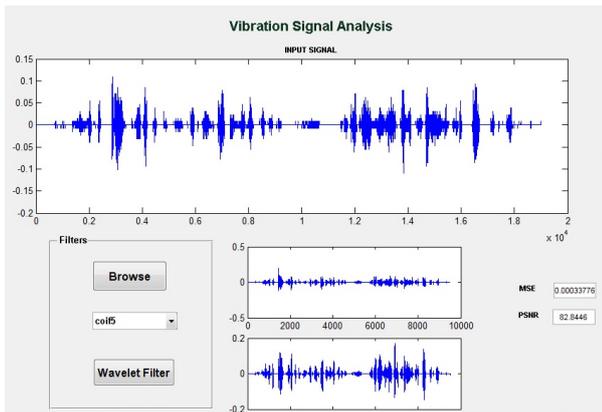


Figure 3. Output Result- Coiflets wavelet

3. Analysis by Daubechies wavelet:

Daubechies wavelet:

The Daubechies wavelets, based on the work of Ingrid Daubechies, are a family of orthogonal wavelets defining a 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 the father wavelet) which generates an orthogonal multiresolution analysis.

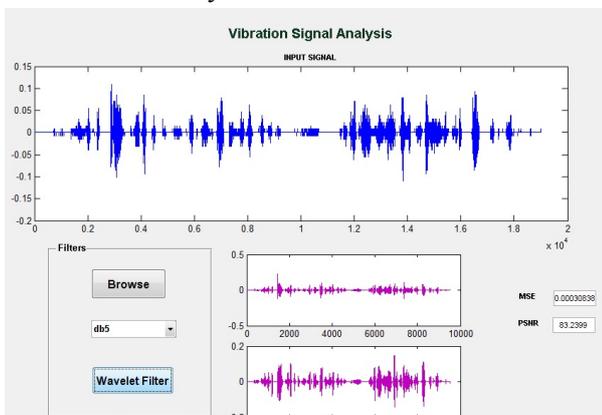


Figure 4. Output: Daubechies wavelets

4. Analysis by Biorthogonal wavelet:

Bior Wavelet

It is well known that bases that span a space do not have to be orthogonal. In order to gain greater flexibility in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi-orthogonal, biorthogonal or non-orthogonal wavelet bases. Biorthogonal Wavelets are compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. In the biorthogonal case,

rather than having one scaling and wavelet function, there are two scaling functions that may generate different multiresolution analysis, and accordingly two different wavelet functions. The dual scaling and wavelet functions have the following properties:

1. They are zero outside of a segment.
2. The calculation algorithms are maintained, and thus very simple.
3. The associated filters are symmetrical.
4. The functions used in the calculations are easier to build numerically than those used in the Daubechies wavelets.

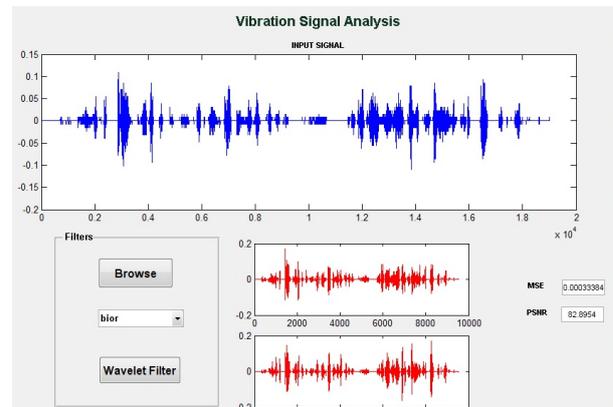


Figure 5. Output Result- Bior wavelet

5. Analysis by Symlet wavelet:

Symlet wavelet

In applied mathematics, symlet wavelets are a family of wavelets. They are a modified version of Daubechies wavelets with increased symmetry.

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. Here are the wavelet functions ψ . You can obtain a survey of the main properties of this family by typing `waveinfo('sym')` from the MATLAB command line. See Symlet Wavelets: `symN` for more detail.

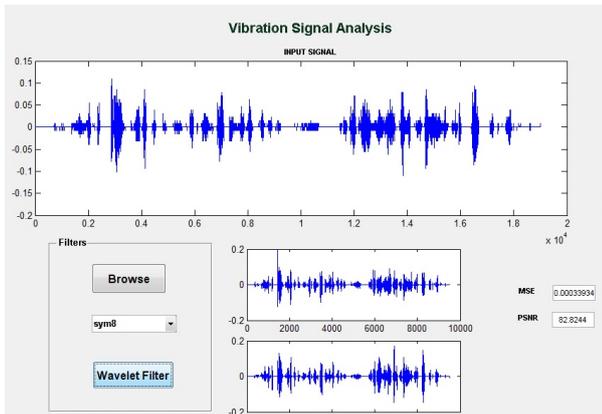
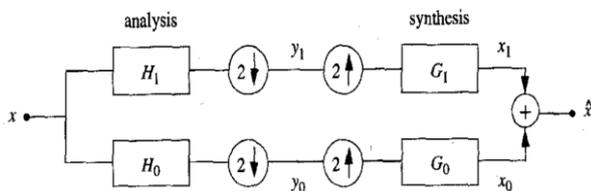


Figure 6. Output Result Symlet wavelet

V. Mathematical Analysis by Wavelet Transform

Filter bank is the building block of discrete-time wavelet transform

For 1-D signals, two-channel filter bank is depicted below



$$H_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m(z) \quad (1)$$

$$L_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot t_m(z) \quad (2)$$

- It converts an input series x_0, x_1, \dots, x_m , into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length $n/2$ each) given by:
- where $s_m(z)$ and $t_m(z)$ are called wavelet filters, K is the length of the filter, and $i=0, \dots, [n/2]-1$.

Calculation of Peak Signal to Noise Ratio And Mean Square Error:

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right)$$

Where R (row=255) is the maximum fluctuation in the input signal.

$$MSE = \frac{\sum_{M,N} [I_1(m, n) - I_2(m, n)]^2}{M * N}$$

Where, M and N are the number of rows and columns in the input signal respectively.

$I_1(m, n)$ and $I_2(m, n)$ are the two input signal.

Tabular form PSNR:

Sr No.	Signal	haar	Coif5	db5	bior	Sym8
1	band0	67.26 78	64.04 24	63.77 63	63.886 6	64.04 06
2	band1	85.14 55	82.27 23	82.34 19	82.112 2	82.13 55
3	band2	85.84 13	82.84 46	83.23 99	82.895 4	82.82 44
4	band3	85.924	83.24 41	83.44 92	83.330 5	82.82 44

Tabular form MSE:

Sr No.	Input Signal	haar	Coif5	Db5	bior	Sym8
1	band0	0.01219832 5	0.0256352 25	0.0272552 52	0.0265715 25	0.025646222
2	band1	0.00019885 2	0.0003853 42	0.0003792 23	0.0003998 16	0.000397625
3	band2	0.00016941 4	0.0003377 66	0.0003083 83	0.0003338 41	0.000339344
4	band3	0.00033934 4	0.0003080 88	0.0002938 86	0.0003020 14	0.000339344

VI. Graphical PSNR comparison

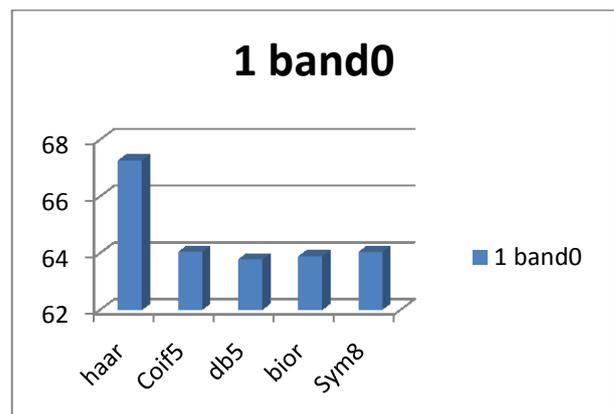


Figure 7. PSNR for band0 signal

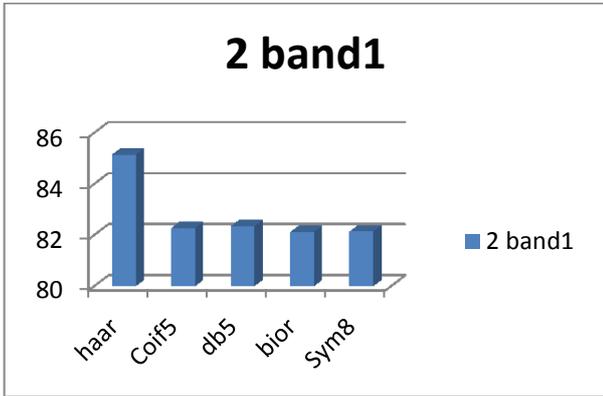


Figure 8. PSNR for band1 signal

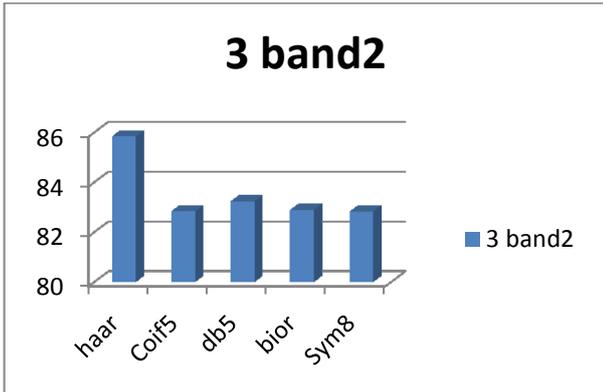


Figure 9. PSNR for band2 signal

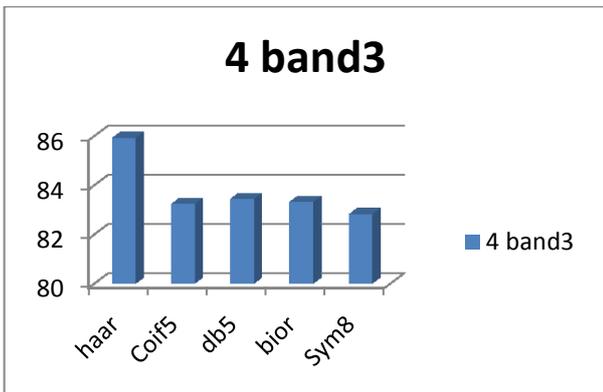


Figure 10. PSNR for band3 signal

VII. Graphical MSE comparison

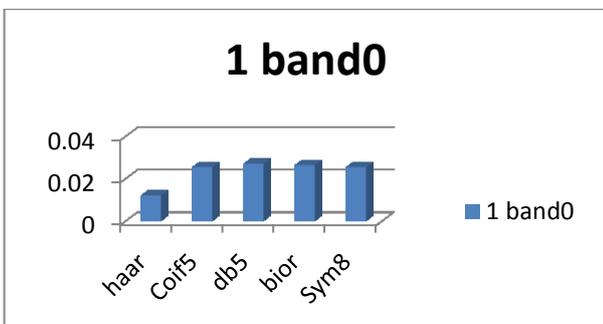


Figure 11. PSNR for band0 signal

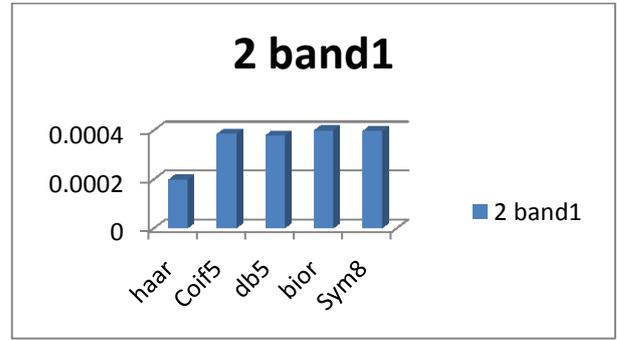


Figure 12. PSNR for band1 signal

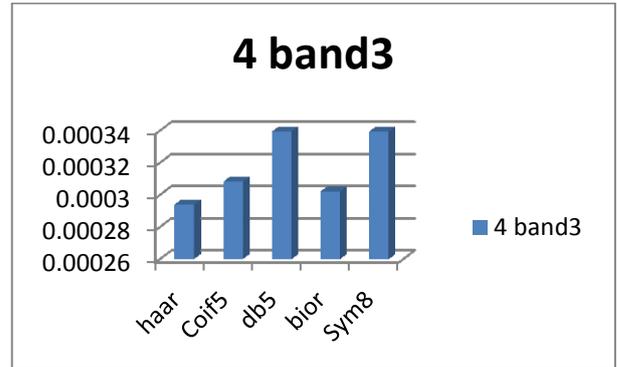


Figure 13. PSNR for band2 signal

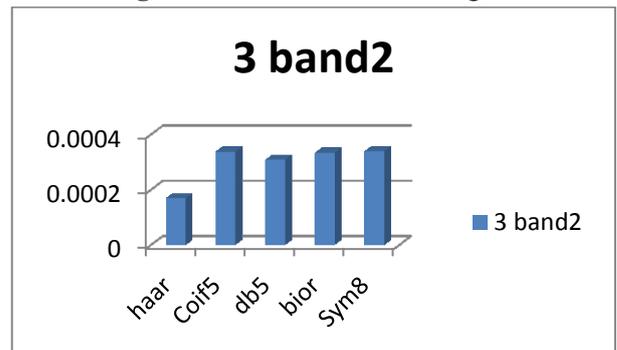


Figure 14. PSNR for band3 signal

VIII. CONCLUSION

Analysis of vibration signal and the results of the investigation demonstrate the components of signal. The results of testing various popular types of the WT show different values of PSNR and MSE. From the result we conclude that,

- ❑ In this project work, five wavelets are implemented. From result we conclude that
- ❑ Peak signal to noise ratio is better in Haar wavelet transform as compared to other wavelets
- ❑ Mean Square Error is also less in Haar wavelet transform
- ❑ Wavelet Transform method is better to analyze over conventional method.

IX. Applications

- Fault Detection In Auto-industry
- Bearing Fault Detection
- Applications In Petrochemical Industry
- System Monitoring
- Noise Reduction

X. REFERENCES

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