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# PERFORMANCE EVALUATION OF DIFFERENT FILTERING AND DENOISING TECHNIQUES ON NON-STATIONARY SIGNAL

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***Abstract:*** Non-stationary signals don't have constant time period, frequency and have errors or noise while obtaining these signals hence, it is important to denoise these signals with suitable filtering techniques in order to examine them accurately. This paper presents a comparison between the filtering techniques of non-stationary signals by using filters such as FIR, Chebyshev, Butterworth, Moving Average and denoising techniques like Wavelet Transform (WT), Empirical Mode Decomposition (EMD) and Wavelet Packet Transform (WPT) for which the methodologies are also discussed. All the techniques were given the same signal from sample non-stationary signals, one at a time. The sample non-stationary signals which were used for this research are VibroArthoGraphic (VAG) signals which were obtained from vibrations of knee joints. Comparison of different techniques is based on performance parameters - Signal to Noise Ratio (SNR) and Mean Squared Error (MSE) of the original signal with the denoised signal. The denoising and analysis of the sample signals were performed in MATLAB software.

***Index Terms* - Vibroarthographic signals (VAG), FIR, Chebyshev, Butterworth, Moving Average Filter, Wavelet Transform (WT), Empirical Mode Decomposition (EMD) and Wavelet Packet Transform (WPT), Mean Squared Error (MSE), SNR**

## I. INTRODUCTION

Signal is a physical quantity that is measurable and the naturally obtained signals and signals from engineering applications are usually non-deterministic due to presence of noise. Since these random signals cannot be defined by deterministic time function or be reproduced accurately, they must be examined by statistical methods. The statistics of usual random signals include mean value, variance, correlation function, and higher-order statistics. If these statistics change with respect to time, the signal can be labeled as Non-stationary signal. Non-stationary signals have a varying time period and so, the frequency of the wave changes constantly. The spectral contents for such signals are also not constant. Due to all these imperfections these signals can’t be used to infer correct results. Electroencephalography (EEG) and VibroArthoGraphic (VAG) are non-stationary signals. The proposed paper will be using VAG signals as reference for non-stationary signals which are obtained from knee joints.

The knee connects the lower leg with the thigh as a synovial joint. The fibula, patella and extensive ligaments make up this joint [5]. The knee joint can undergo mild stress but can be injured in sports and daily activities. Conventional techniques like computer tomography, X-rays, and magnetic resonance imaging (MRI) cannot discover small changes in the early stages of the disease [6], also in case of severe pathological knee joint conditions arthroscopy is inefficient to diagnose it.

The features extracted from Vibroarthographic (VAG) signals can be analyzed to accurately classify between abnormal and normal signals. But for development of methods to generate accurate results, the processed VAG signals must be free from noise. However, signals in the real world are contaminated with noise [7]. Commonly observed noise inherent in non stationary signals are: (i) Baseline Wander, that is introduced during the signal recording of dynamic knee movement cycle and (ii) Random Noise, which is generated because of the recording systems and also due to other environmental factors. Therefore, these signals must be precisely denoised in order for the features that are recovered to contain only the signal's essential information. Hence, we must choose the methods which are compatible with non-stationary signals.

There are many methods to denoise VAG signals like denoising using FIR filters, using Chebyshev filter, using Butterworth filter, using Moving Average filter, Empirical Mode Decomposition and Wavelet Transform. This paper is focused to evaluate the mentioned denoising methods on the same VAG signals using Mean Squared Error (MSE) and Signal to Noise ratio (SNR) as the performance parameters.

## II. FILTERING METHOD

### 2.1 Finite Impulse Response (FIR) : Window filter

Impulse response of the FIR filter is of finite period, eventually it goes down to zero in a finite period of time. Output from the digital FIR filter is obtained from the convolution of input signal and impulse response. Impulse response is acquired in the frequency domain. FIR filter equation [8] is given as:

$$Y(n) = \sum_{k=0}^{N-1} h(k) * x(n-k) \qquad (1)$$

Where Y(n) is output, sample corresponding to input sample x(n), h(k) is filter coefficient or the impulse response and x(n-k) is known as tap. N represents the filter's order.

An abnormal VAG signal was operated on with Low pass FIR window filter. Window used was Hamming [9] with sampling frequency (Fs) 100 Hz and cutoff frequency (Fc) 20 Hz.

### 2.2 Moving Average Filter

The Moving Average Filter is a straightforward type of Low Pass Filter. The working of the filter is simple: the moving average filter takes the average of the last M number of entries in the input signal and averages them to produce a single output [10]. The equation for Moving Average Filter is expressed as:

$$Y(i) = \left(\frac{1}{M}\right) * \sum_{j=0}^{M-1} x(i+j) \qquad (2)$$

Here, Y is the denoised output, M is the window size and y is the noisy input.

The window size (M), or the number of prior signal entries that can be averaged together, is the only actual parameter that can be adjusted in a moving average filter. The signal could still become highly noisy if the window is too small. However, if the window is too big, important signal information could be missed. The ideal window size must be determined through trial and error. Convolution with a very basic kernel is used to create a moving average filter. For example, the filter kernel for the moving average filter with M= 5 will be as follows: 0, 0, 1/5, 1/5, 1/5, 1/5, 0, 0,…

### 2.3 Infinite Impulse Response (IIR) : Chebyshev Filter

Chebyshev filters are used to differentiate the frequency band from one another. There is ripple in the passband which is equal to half of the order of the filter. Transition from passband to stopband is very high. Square of the magnitude [11] response is given as:

$$H(j\omega) = 1/(1 + \varepsilon^2 C_N^2 \left(\frac{\omega}{\omega_P}\right)) \qquad (3)$$

An abnormal signal was given as input to the fifth order Chebyshev filter with sampling frequency (Fs) 100 Hz and cutoff frequency (Fc) 20 Hz.

### 2.4 Infinite Impulse Response (IIR) : Butterworth Filter

Butterworth filter is also recognized as “maximally flat magnitude filter” because it has flat response in the pass band. There are no ripples in the pass band even if the order is increased. There are no ripples in the stop band either. Roll off rate [12] is -20n dB/decade in this filter. Quality factor of the Butterworth filter is 0.707. Squared of the magnitude response is given as:

$$H(j\omega) = 1/(1 + \varepsilon^2 \left(\frac{\omega}{\omega_c}\right)^{2n}) \qquad (4)$$

Where  is operating frequency, n is the order of the filter, c is cut off frequency and  is maximum pass band gain.

Abnormal VAG signal is given as input to the Butterworth filter of fifth order with sampling frequency (Fs) 100 Hz and cutoff frequency (Fc) 20 Hz.

## III. DENOISING METHOD

### 3.1 Empirical Mode Decomposition: EMD

The EMD algorithm is a data-adaptive technique which involves decomposing input signals into a collection of components called Intrinsic Mode Functions (IMF), where the IMF is the function which satisfies the two conditions [13]. The number of both extrema and zero-crossings must always be equal or no more than one apart throughout the data set and mean value of the envelope which is described by local maxima and local minima will always zero. The following is the EMD procedure for a signal [14]:

1. Extrema Extraction
2. For upper and lower envelopes, cubic spline lines that interpolate the local maxima and local minima are used.
3. Calculation of mean value of the envelopes and obtaining Prototype mode (proto-IMF).
4. When it satisfies the first two requirements, this function is regarded as an IMF.

$$x(t) = \sum_{i=1}^{I} c_i + r_I \qquad (5)$$

Finally, we will get a decomposition of the signal (y(t)) into I IMFs where $c_n$ is the $n^{th}$ component of signal which consist of various frequency bands which are ranging from low to high and a residue $r_I$, which is the mean trend of y(t) (Original signal). Each frequency band has distinct frequency components that change in response to changes in signal y(t).

### 3.2 Wavelet Transform: WT

Wavelet Transform is a type of time-frequency analysis technique which uses a time interval to analyze the high and low frequency components of the given signal. The fundamental principle of the Wavelet Transform [15] is to utilize the basis function to divide the signal into smaller sub signals which will have various frequency bands and then the data using WT can be divided into detail signal and approximate signal with the help of given basis function. The low frequency part is shown by approximate signal and the high frequency part is shown by the detail signal of the original signal respectively, next, based on the necessary number of decomposition layers, the detail signal is divided (we have used 3 decomposition layers).(we have used 3 decomposition layers). The next step is denoising the signal using threshold technique [16], where it is very important to select the right threshold method and calculation (we have used soft-Universal Thresholding method) and finally the signal is reconstructed.

$$X_{a,b} = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \qquad (6)$$

Where a is the scaling factor, b is the translation factor, ψ is an arbitrary mother wavelet (we have selected "sym4" as the mother wavelet), and x(t) is the real signal (X is the processed signal). The scale and window size are identical.

### 3.3 Wavelet Packet Transform: WPT

A Wavelet Transform is generalized into a so-called Wavelet Packet Transform. The signal is divided into high frequency and low frequency bands during wavelet packet decomposition. Additionally, dependent on the degrees of decomposition, these high frequency and low frequency components are split into numerous sub bands. The wavelet packet decomposition generates '2n' unique sets of coefficients for 'n' layers of decomposition [17]. The standard wavelet packet denoising procedure is as follows: 1) choosing the right wavelet foundation (we have used 'sym1'), figuring out how many levels of decomposition to use (we have used 3 layers of decomposition), and performing wavelet packet decomposition. 2) Calculating the best decomposition tree, then selecting the best wavelet packet basis after providing the entropy standard (we have used 'Shannon' criteria). 3) selecting an appropriate threshold technique (we have used 'Universal Thresholding') to quantize the wavelet packet decomposition coefficients. 4) reconstructing the signal back together [18].

## IV. Evaluation Parameters for Filtering and Denoising Techniques

### 4.1 Mean Squared Error (MSE)

Mean Squared Error is a technique which finds the amount of error in a given model. MSE is equal to zero indicates that zero error is present in the model. MSE is used to calculate the accuracy of denoising. Smaller value of MSE indicates better accuracy or denoising. MSE is inversely proportional to signal to noise ratio (SNR). MSE measures the noise power in PSNR which is the signal process quality of the estimator. The MSE can be formulated as:

$$MSE = \sum_{n=1}^{N}(y(n) - y'(n))^2/N \qquad (7)$$

Where N is the number of samples, and y(n) and y'(n) are the denoised and noisy signals, respectively.

### 4.2 Signal to noise ratio (SNR)

SNR is a measure to calculate the efficiency and performance of a particular denoising method. SNR is inversely related to Mean squared error. SNR [19] is formulated as:

$$SNR = 10log_{10}\frac{\sum_{n=1}^{N} y(n)^2}{(y(n)-y'(n))^2} \qquad (8)$$

## V. Results And Conclusion

Sample VAG signals which are obtained from knee joints were used for comparison of different filters and denoising techniques. Sample signals contain few Normal and few Abnormal signals which after denoising were compared by performance parameters: Signal to Noise Ratio (SNR) and Mean Squared Error (MSE) calculated for different methods. Waveforms of the original signal and filtered output signal from different techniques are shared in this paper.

Fig. 1 Shows the one of the original VAG signal from the sample dataset, fig. 2, 3, 4 & 5 shows the output of different filters - FIR, Moving Average (MA), Chebyshev and Butterworth Filters respectively when applied on the original signal whereas fig 6, 7 & 8 shows the output of different techniques – Empirical Mode Decomposition (EMD), Wavelet Transform (WT) and Wavelet Packet Transform (WPT) respectively when applied on the same signal.

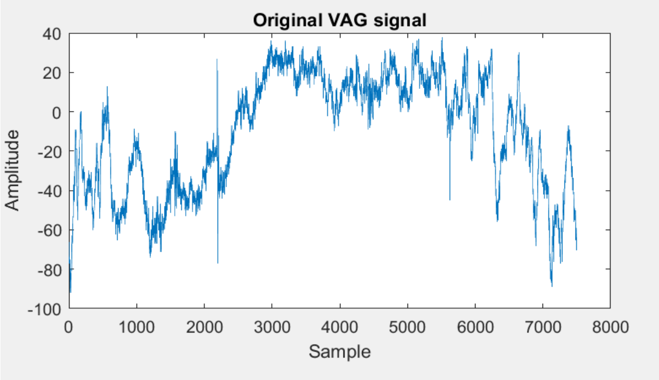


Fig. 1. Original VAG signal

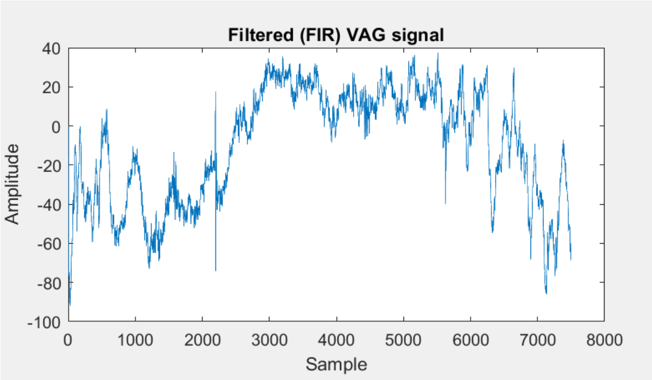


Fig. 2. Filtered (FIR) VAG signal

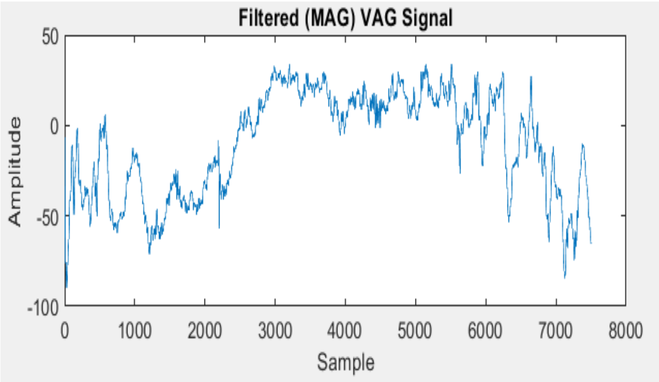


Fig. 3. Filtered (Moving Average) VAG signal

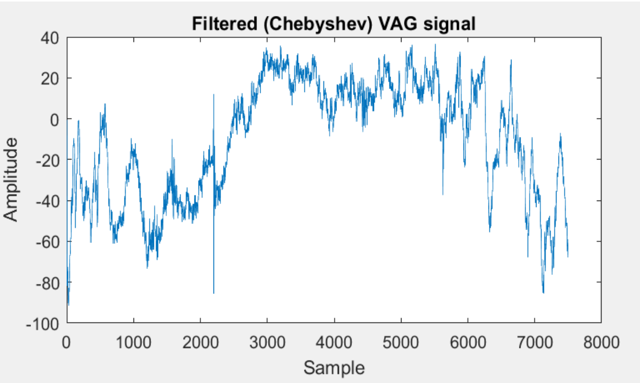


Fig. 4. Filtered (Chebyshev) VAG signal

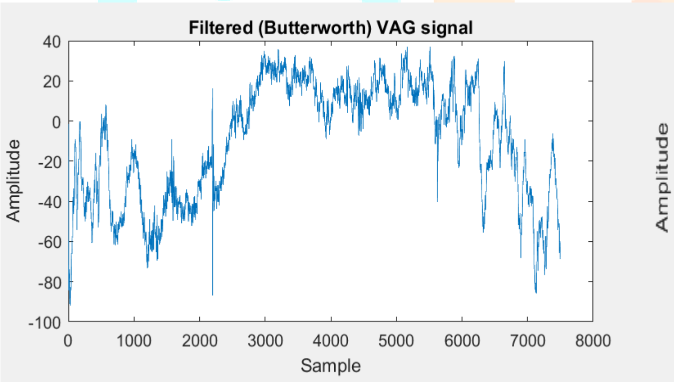


Fig. 5. Filtered (Butterworth) VAG signal

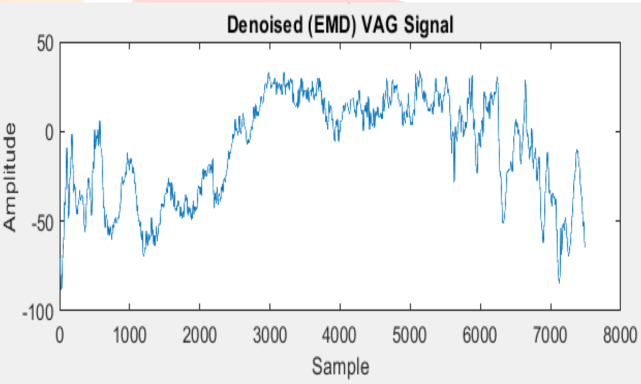


Fig. 6. Filtered (EMD) VAG signal

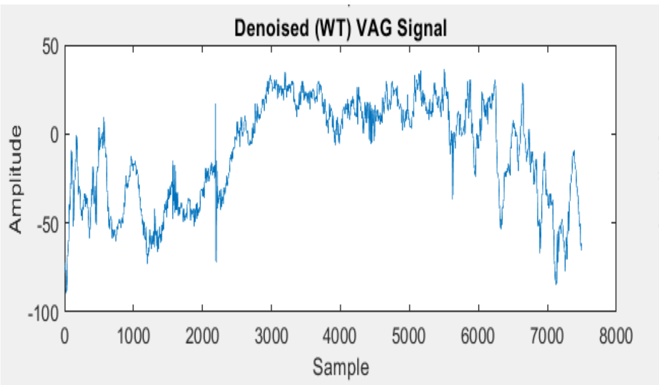


Fig. 7. Filtered (WT) VAG signal

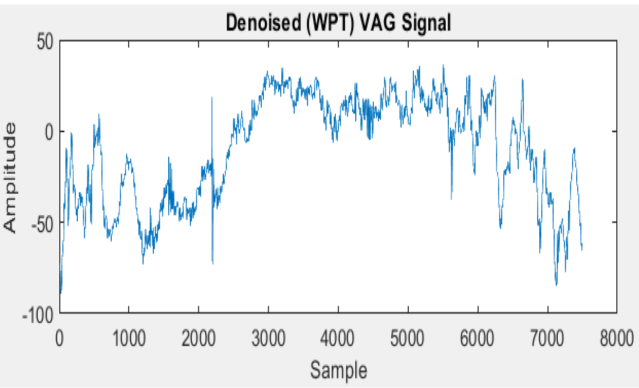


Fig. 8. Filtered (WPT) VAG signal

*Table 1*

| Filter and denoising method | SNR | | Mean square Error | |
|---|---|---|---|---|
| | Normal1 | Abnormal1 | Normal1 | Abnormal1 |
| FIR | 10.0084 | 17.2124 | 60.6598 | 17.7578 |
| Chebyshev | 9.1839 | 16.2024 | 72.4143 | 22.3809 |
| Butterworth | 9.9653 | 17.2366 | 60.5810 | 17.6957 |
| Moving Average | 12.3901 | 19.6718 | 34.1348 | 10.0484 |
| EMD | 9.95455 | 19.78801 | 62.4195 | 9.866440 |
| Wavelet Packet Transform | 13.6726 | 23.1859 | 25.3425 | 4.4841 |
| Wavelet Transform | 18.0628 | 28.9477 | 9.4098 | 1.1941 |

*Table 2*

| Filter and denoising method | SNR | | Mean square Error | |
|---|---|---|---|---|
| | Normal2 | Abnormal2 | Normal2 | Abnormal2 |
| FIR | 8.9317 | 10.5889 | 16.7655 | 16.3707 |
| Chebyshev | 8.0827 | 9.8246 | 20.2772 | 19.4826 |
| Butter-worth | 9.0350 | 10.6230 | 16.7655 | 16.3592 |
| Moving Average | 11.2467 | 13.0177 | 9.6319 | 9.2261 |
| EMD | 8.022149 | 11.461182 | 21.3785 | 13.708461 |
| Wavelet Packet Transform | 12.6441 | 14.0207 | 6.9675 | 7.2974 |
| Wavelet Transform | 16.2922 | 17.7366 | 3.0698 | 3.1485 |

*Table 3*

| Filter and denoising method | SNR | | Mean square Error | |
|---|---|---|---|---|
| | Normal3 | Abnormal3 | Normal3 | Abnormal3 |
| FIR | 5.4534 | 10.3145 | 33.6905 | 31.2077 |
| Chebyshev | 4.9803 | 9.2296 | 38.0262 | 39.9610 |
| Butter-worth | 5.2963 | 10.3025 | 35.8655 | 31.6004 |
| Moving Average | 8.1380 | 12.7575 | 17.3229 | 17.4778 |
| EMD | 7.583658 | 12.216036 | 22.0553 | 20.4944 |
| Wavelet Packet Transform | 11.9293 | 18.8028 | 7.4953 | 4.3983 |
| Wavelet Transform | 16.1950 | 26.5894 | 2.9101 | 0.7443 |

The above tables - table 1, table 2 and table 3 shows the value of SNR and MSE for the denoised abnormal and normal VAG knee joint signals calculated for different methods.

It is evident from the tables that the values of the SNR are better for the signals filtered using denoising techniques (EMD, WT and WPT) than the SNR's obtained from filtering techniques. Also, the values of MSE are lower for the signals filtered using denoising techniques (EMD, WT and WPT) than the MSE's obtained from filter techniques. The denoising technique that relatively performed well was the Wavelet Transform (WT) Technique. Thus, inference can be made that denoising techniques (specially Wavelet Transform WT) are better than filtering techniques on non-stationary signals.

## VI. Acknowledgement

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