Minimization of artifacts in wrist pulse signals using signal processing techniques

B Shreyas
bshreyas.2196@gmail.com
Dayananda Sagar College of Engineering, Bengaluru, Karnataka

Abhishek M R
abhishekmr1997@gmail.com
Dayananda Sagar College of Engineering, Bengaluru, Karnataka

S Hema Priyadarshini
priyadhema@gmail.com
Dayananda Sagar College of Engineering, Bengaluru, Karnataka & SBST, Vellore Institute of Technology, Vellore, Tamil Nadu

Dr. Anand Prem Rajan
janandpremrajan@vit.ac.in
SBST, Vellore Institute of Technology, Vellore, Tamil Nadu

ABSTRACT

Pulse pressure is a manifestation of arterial palpation of the heartbeat. Wrist pulse signal contains important information about the health status of a person and pulse signal diagnosis has been employed in oriental medicine for a very long time. This paper mainly addresses the problem of removing artifacts from wrist pulse signals. Noise is an irregular function that accompanies a transmitted electrical signal and tends to obscure it. The collected wrist pulse signals contain noise. The type of noise which the signal contains may be random noise, structured noise or physiological interference. In our paper, we have employed signal processing techniques in order to remove noise from the wrist pulse signal. Low Pass Filter (LPF) and Wavelet Transform (WT) techniques are used for this purpose. In our work, we have considered simulation and actual cases. In simulation cases, we have added noise to the signal and tried to remove it. In actual cases, we have considered the results of the simulation and implemented the signal processing techniques on actual noisy wrist pulse signals. Our work has studied the efficacy of LPF and WT techniques in minimizing artifacts in wrist pulse signals in simulation and in actual cases. Calculated mean square error for a simulated signal show that wavelet denoising has lesser mean square error than low pass filtering. Hence we have concluded that wavelet denoising is a better filtering than low pass filter.

Keywords— Wrist pulse signals, Artifacts, Low pass filter, Wavelet transform, Mean square error, Denoising

1. INTRODUCTION

The sudden transmission of blood resulting in an abrupt expansion of artery results in Pulse. Pulse is examined at the radial artery. These pulse signals are generally acquired on the wrist [1]. The science of pulse is called as 'Nadi Vijnana' (Sphygmology) [2].

Noise is an error or undesired random disturbance in a user information signal. The noise is a summation of unwanted or disturbing energy from natural and sometimes man-made sources [3]. Noise is also typically distinguished from distortion, which is an unwanted systematic alteration of the signal waveform caused by the equipment [4] [5]. The types of noise which get added to a signal may be random noise, structured noise or physiological interference [6]. The signals obtained from the sensors contain many frequency components measured unrelated needed to be get rid of through filter circuit. The realizable filters that are in common use are the Butterworth filter, Chebyshev filter, and Bessel filter. Low order Butterworth low pass filter has rapid response, small overshoot but bad in test precision, while high order Butterworth low passes filter is good in test precision but has slow response, large overshoot and poor stability [7]. A kind of new high order Butterworth low pass filter, which the angle T is destined for a constant and the remaining poles are evenly distributed among the Butterworth circumference of the complex plane, has been put forth. The improved Butterworth low pass filter is implemented in this paper. Compared with the conventional Butterworth low pass filter of the same order, the improved Butterworth low pass filter has a more rapid response, smaller overshoot. This kind of filter can be used to enhance the test precision.

The wavelet transform and its implementation for discrete signals are reviewed briefly. A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero [8]. Unlike the sines used in Fourier transform for decomposition of a signal, wavelets are generally much mor e concentrated in time. They usually provide an analysis of the signal which is localized in both time and frequency. One of the fields where wavelets have been successfully applied is data analysis. Beginning in the 1990s, wavelets have been found to be a powerful tool for removing noise from a variety of signals (denoising) [9]. They

allow us to analyze the noise level separately at each wavelet scale and to adapt the denoising algorithm accordingly. Wavelet thresholding methods for noise removal, in which the wavelet coefficients are thresholded in order to remove their noisy part [10].

2. METHODOLOGY

2.1 Low Pass Filter
Low pass filter is a filter that allows only low-frequency signals to pass through and stops the high-frequency signals. These low pass filters are used in many signal sending/ receiving systems to allow desired frequencies to pass [11]. The exact frequency response of the filter depends on the design and type of the filter. The desired filter is obtained from the prototype by scaling for the desired bandwidth and impedance and transforming into the desired bandwidth.

2.1.1 Butterworth Filter
A Butterworth filter (LPF) has a flat response in the passband and steep slope soon after cutoff (maximum flat filter) in ideal conditions [12]. This is done by combining high Q section and low Q section. Four and eight-pole Butterworth filters are commonly used. This filter exhibits a monotonically decreasing transmission with all transmission zeroes at $\omega=\infty$, making it an all-pole filter.

The magnitude function for an Nth-order Butterworth filter with a passband edge ω is given by:

$$|T(j\omega)| = \frac{1}{\sqrt{1+\varepsilon^2(\frac{\omega}{\omega_p})^{2N}}} \qquad (1)$$

$$\text{at } \omega = \omega_p \qquad |T(j\omega_p)| = \frac{1}{\sqrt{1+\varepsilon^2}} \qquad (2)$$

The parameter ε determines the maximum variation in passband transmission, A_{MAX} (i.e., passband ripple):

$$A_{MAX} = 20\log(\sqrt{1+\varepsilon^2}) \text{ and } \varepsilon = \sqrt{10^{\frac{A_{MAX}}{10}} - 1} \qquad (3)$$

At the edge of the stopband, $\omega=\omega_s$,

$$A(\omega s,) = -20\log(\frac{1}{\sqrt{1+\varepsilon^2(\frac{\omega}{\omega_p})^{2N}}}) \qquad (4)$$

The above equation is used to determine the filter order required, which is the lowest value of N that yields $A(\omega_s) \geq A_{MIN}$.

2.2 Wavelet Denoising
The Discrete Wavelet Transform (DWT) of a signal x(t) which is one-dimensional is computed by convolving it through a series of low and high pass filters. If we denote *'g'* as the impulse response of a low pass filter and '*h*' as the impulse response of a high pass filter, then we compute the DWT coefficients as follows:

$$y_{low}[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \qquad (5)$$

$$y_{high}[n] = (x * h)[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] \qquad (6)$$

Where we call y_{low} as the approximation coefficients and y_{high} as the detail coefficients [13]. Since in each case half the frequencies have been dropped, then half the samples in y_{low} and y_{high} can be removed according to Nyquist-Shannon sampling theorem. This process can be repeated taking y_{low} as the signal, and iteratively splitting it into approximation and detail coefficients [14]. In a case where we treat the signal is a 3-D data cube as shown in Fig -1, each axis which is Axis0 and Axis1 can be treated separately, i.e., we apply the Low

Decomposition Filter (Lo_D) and High Decomposition Filter (Hi_D) plus the downsampling ($2 \downarrow 1$) through the Axis0 first, and then repeat this procedure for Axis1.
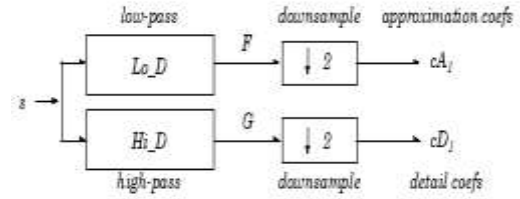

Fig. 1: One-dimensional wavelet denoising

The one-dimensional wavelet denoising follows the following three steps:
1) One-dimensional signal wavelet decomposition: Selecting a wavelet basis function and to determining the decomposition level N.
2) High-frequency coefficient threshold selection: Each layer from the first layer to layer N, the high-frequency coefficients are used to select a threshold quantification processing.
3) One-dimension wavelet reconstruction: The reconstruction is done according to the low-frequency coefficients of the wavelet decomposition of the layer N and high-frequency coefficients through quantization processing of the first layer to the layer N.

In the wavelet denoising steps discussed above, the most critical is step 2 viz. how to choose the threshold quantization thresholds and how it is directly related to the quality of the signal denoising [15]. There are three common threshold denoising method: Forced threshold denoising, default threshold denoising, and the soft/hard threshold denoising. In the forced threshold denoising the high-frequency coefficients in the wavelet decomposition structure of all set to zero, although this method is simple and the reconstructed signal is also relatively smooth, after denoising useful components of the signal is lost. The soft/hard threshold denoising with empirical and human subjectivity is very tedious and time-consuming [16]. Due to these disadvantages of the two methods, we have chosen the default threshold denoising in this paper. In this method, the threshold generated by the system is fixed. The coefficient deletion is less than the threshold and then the signal reconstructed and the results are given.

3. RESULTS AND DISCUSSIONS
In this paper, we have considered wrist pulse signals acquired through an instrument called Nadi Tharangini. We have 20 noisy wrist pulse signals which have been acquired from patients.

For our analysis we have considered two cases, one is the simulation case and the other is the actual case. For simulation cases, we have taken noiseless wrist pulse signals, added noise to it and tried to remove it using signal processing techniques. On considering the results of the simulation cases we have applied the denoising techniques used for the simulation of the actual wrist pulse signals

3.1 Results of denoising of simulated signals using LPF
We have considered a noiseless wrist pulse signals for simulation. This simulation is done by adding a 50 Hz noise (sine wave) to the noiseless wrist pulse signal. Now, this signal has been passed through a Butterworth low pass filter of 5th order and 20 Hz cut-off frequency.
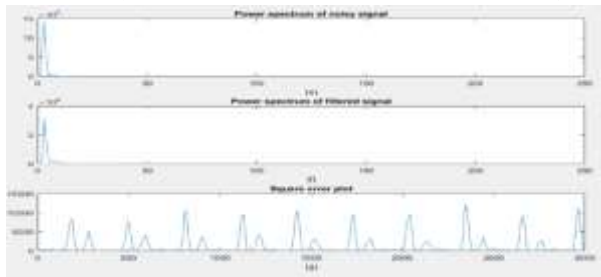
Fig. 2: Sine wave simulation

As we can see in Fig -2 the 50 Hz noise (sine wave) added was mostly removed using the low pass filter.

For the above filtering, we have calculated mean square error by varying frequency and amplitude. The equation for mean square is given by,

$$e(n) = \frac{1}{N}\sum_0^N[x(n)^2 - y(n)^2] \qquad (7)$$

Where, e(n)= mean square error
        y(n)= filtered signal
        x(n)= actual signal
        N= number of samples

Table 1: Mean square error of added sine noise

S. No	Amplitude of noise	Mean square error
1.	10	5485
2.	25	5720
3.	50	6610
4.	75	8126

As we can see in Table-1 the mean square error increases as the amplitude of the noise increases.

We have now added White Gaussian noise. Gaussian noise is generated by a set of randomly generated numbers.
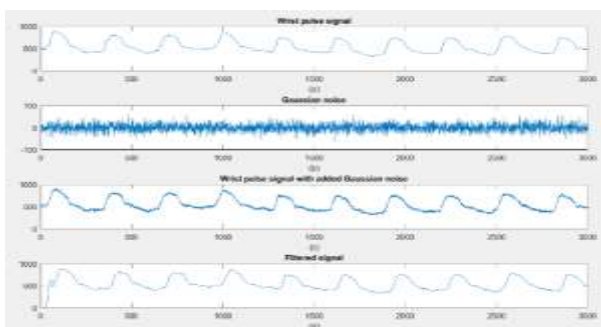

Fig. 3: Gaussian noise simulation

As we can see in Figure 3 the power spectrum shows that the frequency components above the filter cut-off have been

removed. As the Gaussian noise cannot be removed completely by the low pass filter, the square error plot shows high amplitude spikes at different points.

Table 2 shows the mean square error of the filtered signal. Here we have increased the power of the Gaussian noise and measured the mean square error.

Table 2: Mean square error of added Gaussian noise

S. No.	Gaussian noise power	Mean square error
1.	10	15172
2.	20	15193
3.	30	15220
4.	40	16799

As we can see in Table 2, the mean square error value increases as the power of the Gaussian noise increases.

3.2 Results of denoising of simulated signals using WT
We have added White Gaussian noise to the wrist pulse signal of 3000 samples. Now we have applied 1-D wavelet transform to the noise added wrist pulse signal.
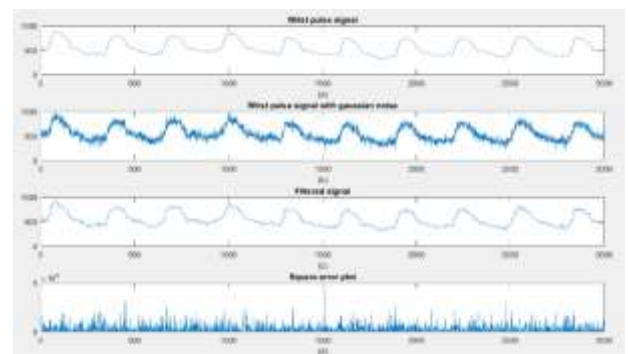

Fig. 4: Simulation using WT with added Gaussian noise

As we can see from Figure 4 the wavelet transform is very effective in removing noise from the wrist pulse signal.

Table 3 shows the mean square error of the wavelet transform. The power of the Gaussian noise is increased and the mean square error is calculated.

Table 3: Mean square error of added Gaussian noise simulation of WT

S. No.	Gaussian noise power	Mean square error
1.	10	41.4
2.	20	141.4
3.	30	658.7
4.	40	1154.8

From the Table 3 we can say that the mean square error increases as the power of the Gaussian noise increases.

Table 4 shows the comparison between the mean square error of low pass filtering and Wavelet transform.

Table 4: Comparison of mean square error of LPF and WT

Gaussian noise power	Low pass filter	Wavelet transform
10	369.3	41.4
20	525.9	141.4

3.3 Comparison of LPF and WT denoising
Now we have compared the filtering results of low pass filter and wavelet transform. The simulation is done by adding

white Gaussian noise to clean wrist pulse signals and filtering them. Figure 5 and Figure 6 shows the simulation using Gaussian noise using a low pass filter and wavelet transform.
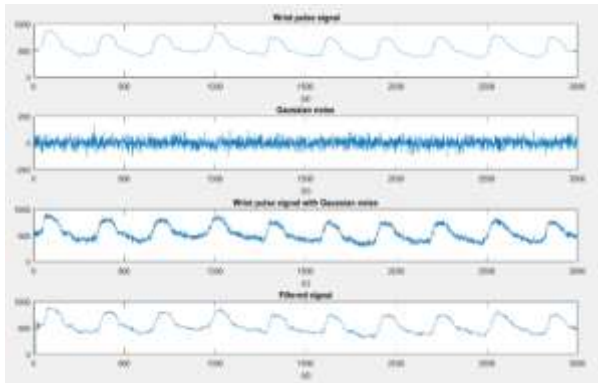

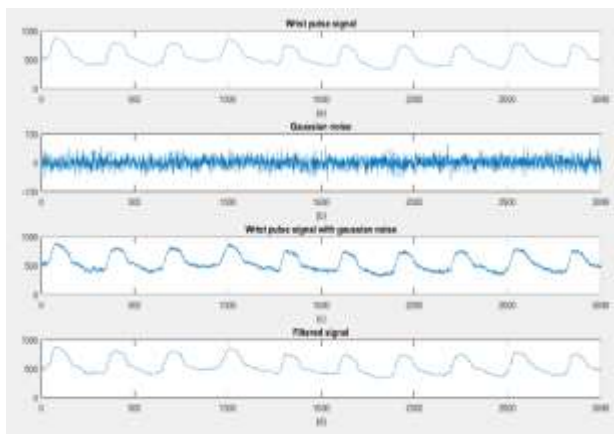**Fig. 5: Gaussian noise filtering using a low pass filter**

Fig. 6: Gaussian noise filtering using wavelet transform

3.4 Comparison of LPF and WT of actual signals
As expected from the simulations the higher frequency components were filtered by the low pass filter. This is shown in Figure 7.
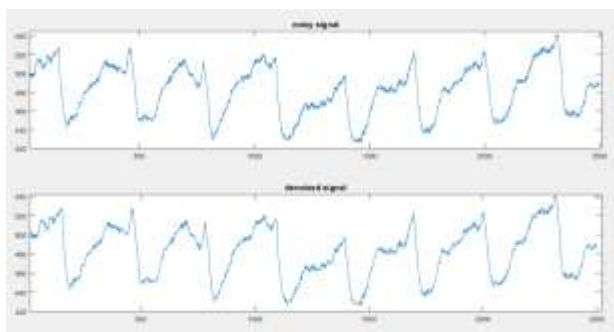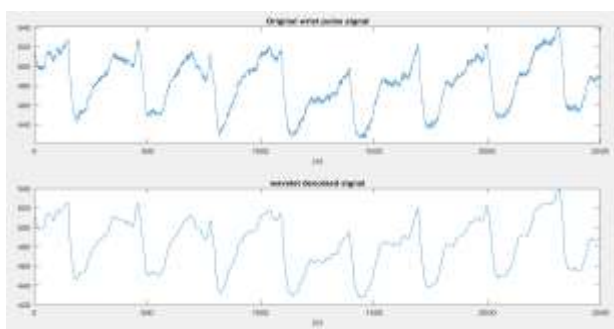

Fig. 7: Low pass filter output

Fig. 8: Filtered wrist pulse signal using wavelet transform

As we expected from the simulations, the wavelet transform is successful in filtering the noise in the wrist pulse signal. This is shown in Figure 8.

4. CONCLUSION
Analyzing the physiological signals like wrist pulse signals becomes difficult if noise components are present. The main objective of this paper is to eliminate noise in wrist pulse signals for better analysis of the pulse signals. The noise removal techniques were implemented and evaluated. The performance of two noise minimization techniques i.e. low pass filtering and wavelet transform were compared using different performance parameters.

In this paper, we have considered simulation and actual cases. For simulation, we have considered noiseless wrist pulse signals upon which noise is added and removed. After verifying the results of the simulation we have implemented this technique on the actual signals.

In our simulations, a low pass filter was able to remove the sine noise added to it. But, it was not satisfactory for the Gaussian noise that was added. Hence we implemented a wavelet transform of the 3rd approximation. Wavelet transform was successful in removing most of the Gaussian noise that was added.

From the experimental results we have concluded that for noise removal in the wrist pulse signal, the wavelet transform technique is the recommended approach as it gives comparatively better results.

5. REFERENCES
[1] "Comparative Analysis of Different Techniques for Removal of Baseline Wander from Wrist Pulse Signals(WPS)", Nidhi Garg, Hardeep S. Ryait, Manu Chopra and Amod Kumar, RAECS UIET Panjab University Chandigarh, 21-22 December 2015.

[2] "Study on Pulse Wave Signal Noise Reduction and Feature Point Identification", 1zhao Zhi-qiang, Zheng Guo-wei, Pang Yu, Shen wei, Liao cheng and Lin Jin-zhao, Journal of Convergence Information Technology(JCIT), Vol. 8, No. 9, May 2013.

[3] "Role of pulse diagnosis: A review", Kaur, R, Chopra, M, Garg, N, Ryait, H.S, Computing, Communication Automation (ICCCA), 2015, International Conference, Vol.6, No.2, pp.152-155, 15-16 May 2015.

[4] "Wavelet-based cascaded adaptive filter for removing baseline drift in pulse waveforms", L. Xu; Zhang, D Kuanquan Wang, Biomedical Engineering, IEEE Transactions on, Vol.52, No.11, pp.1973-1975, Nov 2005.

[5] "Baseline wanders correction in pulse waveforms using wavelet-based cascaded adaptive filter", L. Xu, David Zhang, Kuanquan Wang, Naimin Li, Xiaoyun Wang, Computers in Biology and Medicine, Vol. 37, Issue 5, pp. 716-731, May 2007.

[6] "Wavelet decomposition and feature extraction From pulse signals of the radial artery", M. Sareen, Abhinav, P. Prakash, and S.Anand, International Conference on Advanced Computer Theory and Engineering, ICACTE 2008, Phuket, Thailand, pp. 551-555.2008.

[7] "Motion Artifact Elimination Using Adaptive Filter Based on Wavelet Transform in Pulse wave Measurement", Qiao Xiaoyan, Yao Feng, Dong Youer, IEEE 8th International Conference on Biomedical Engineering, 319-322, 2009.

[8] "Point Detection of Pule Wave Based on Wavelet Transform", Zhang Shi, Du Kai, DONG Jian-Wei, Sign, Journal of Data Acquisition & Processing. 12, Vol. 21, 2006.

[9] "Arterial Blood Pressure Measurement and Pulse Wave Analysis", Subhash K Ohal, R.J.Vaidya, IOSR Journal of Electronics and Communication Engineering, Vol. 4, Issue 3, pp 41-4, Dec 2012.

[10] "A quantitative system for pulse diagnosis in Traditional Chinese Medicine", Huiyan Wang, Yiyu Cheng, Medicine," Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference, Vol.14, pp.5676-5679, 17-18 Jan 2006.

[11] "Comparisons of discrete wavelet transform, wavelet packet transform and stationary wavelet transform in denoising PD measurement data", Zhou X, Zhou C, Stewart B.G, Electrical Insulation, 2006. Conference Record of the 2006 IEEE International Symposium, pp.237-240, 11-14 June 2006.

[12] "Wrist pulse signal classification for health diagnosis", Thakker B, Vyas A.L, Farooq O, Mulvaney D, Datta S, Biomedical Engineering and Informatics (BMEI), 2011 4th International Conference, Vol. 4, pp.1799-1805, 15-17 October 2011.

[13] "Parameter estimation of human nerve C-fibers using matched filtering and multiple hypothesis tracking", Hammarberg, B., Forster, C. and Torebjork, E, IEEE Trans. Biomed. Eng., Vol. 49, pp.329-336, 2002.

[14] "NaXi Pictographs Edge Detection Using Lifting Wavelet Transforsform", Guo Hai, Zhao Jing-Ying, Da Ming-Jun, Journal of Convergence Information Technology (JCIT) Vol. 5, 5, July 2010.

[15] "Spatial feature extraction from wrist pulse signals", Cheng-Ying Chung; Yu-Feng Chung; Yu-Wen Chu; Ching- Hsing Luo, Orange Technologies (ICOT), 2013 International Conference, pp.1-4, 12-16 March 2013.

[16] "Different Techniques of Baseline Wandering Removal - A Review", Sonali, Payal Patial, International Journal of Enhanced Research in Science Technology & Engineering, Vol. 2 Issue 5, May-2013.