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ESTIMATION OF CARDIOVASCULAR DISEASE FROM PPG SIGNAL BY DENOISE USING WAVELET TRANSFORMS

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Abstract - Photoplethysmography uses the infrared radiation to measure the change in the blood pressure. When light travels into the tissue and the biological changes is detected by PPG sensors. It is simple optical method and non-invasive technique. PPG signals are affected by various factors such as motion artifacts and power line noise caused by voluntary or involuntary movements by the patient. Due to these noise effective PPG measurements are not calculated and patients fall under diseased state. So we propose denoising of PPG signals using wavelet transform in this paper. This methodology will remove noise and a greater accuracy of result is obtained. The dataset of the patient is collected and sampling is done. The datasets are fed into wavelet analyzer in Matlab. To demonstrate effectiveness of our proposed methodology, the result of PPG signal after denoising of wavelet transform is compared with PPG signal before denoising. There are various types of wavelet denoising like Haar, Daubechies and Coiflet. The input PPG signal is denoised in all these types of wavelet transforms and every values is tabulated. From these the most effective type of denoising method can be concluded. Our proposed model can be virtually simulated by using Matlab.

***Key Words*:** Photoplethysmography, Non-invasive, PPG signals, Denoising, Wavelet transform, Matlab

1.INTRODUCTION

Today people are suffering from different kinds diseases. Among those one important problem was heart disease. ECG and PPG are used to detect heart disease. In these PPG is an effective and non-invasive method. PPG signal is used to analyze the heart pulse. It used optical technique that is the IR light is passed through the skin and detects the blood pulse rate. It is cost effective technology. In detection of PPG signal motion artifacts and power line noise affects the effective measurements. To avoid this denoising technique is used.

In earlier stages Fourier transform method was used for denoising. Fourier transform has frequency data of the signals that represents its frequencies and their magnitude. It does not provide information that is when these frequency components occur. so this transform is not changing for stationary signals [4]. Stationary signals are ones which doesn't changes with time so they have constant frequency.

So the short time fourier transform is used to change the poor time resolution when comparing with fourier transform. In STFT for an equal area a thin window we will get high time resolution but less frequency resolution. When our window is extensive we will get less time resolution but higher frequency resolution of our signal.

To overcome this wavelet transform, method was used. The wavelet transforms consequences in examining a signal in dissimilar frequencies at various resolutions this method is called as multi-resolution analysis. In wavelet transform the wavelets performances as a window. In this we will able to change the Central frequency and width through varying s. Where s is scaling factor. This is known as scaling. An expandable wavelet has low frequency resolution with bad resolving time. This creates large value of s. Shrunken wavelet has high frequency resolution with low resolving time. This corresponds to small value of s. So with these help of wavelet we can able to change width of the window function which is useful to attain high frequency components and also low frequency components with good resolution. There are different types of wavelet transform. Among these we take Haar, Daubechies and Coiflet [10]. PPG signals a kind of sine waves so we take those wavelets transform for denoising. Figure1.1 shows the PPG signal morphology

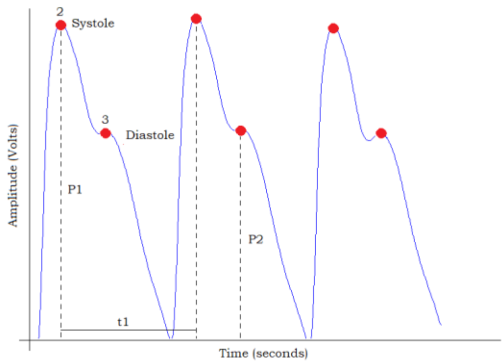

Fig-1.1: Morphology of PPG signal

2.METHODOLOGY

Figure2.1 represents the Flow chart of proposed method. Here the full process of how the input PPG signal is fed into each stages is explanined.

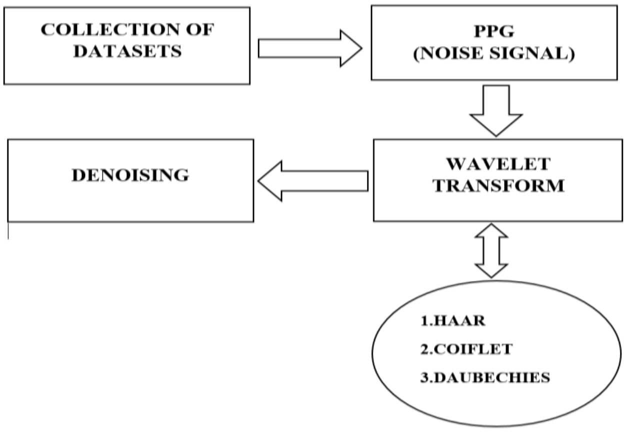

Fig-2.1: Flow chart of proposed method

First the input PPG signal was collected. The Input PPG signals of 42 patients were taken from Capnobase dataset. From those there are 44000 of dataset was present in each patient. It is then divided into 8parts and mean was taken to improve the accuracy. The input PPG signal was analyzed in Matlab. Here we are using 5th level decomposition. It is observed that PPG signals are affected by Gaussian noise and power line noise. Then the PPG signals is decomposed into many stages. Foremost the signal is decomposed into Low pass filter and High pass filter. On further process low pass filter is decomposed to again high pass and low pass filters. Then process will repeat and so on.

Further the Decomposed signals are fed for thresholding to improve the quality of signal. Here there are two types in thresholding ie, soft thresholding and hard thresholding. Then threshold signals are passed into filters. The filters will remove the error signals in which the Input PPG signals containing. The filtered signals then reconstructed back to its old form and ready for denoising. The input signals are fed into wavelet analyzer in Matlab for denoising. After the signals fed into Matlab the required wavelet transform is selected and denoised. To show effectiveness of our proposed methodology, the result of wavelet denoising methodology is compared with PPG signal before denoising [6].

As the PPG signals are sine waves they can be denoised only in certain type of wavelet transforms. The input PPG signal is denoised in wavelet transforms like Haar, Daubechies and Coiflet. The input PPG signals is denoised in all the type of wavelet in different types of decomposition levels. In our proposed model we will clearly show the mathematical result of the best suitable method for denoising of PPG signals. We will tabulate the reading obtained from Input PPG signals of the patient and the brief comparison of all wavelet transform reading. From those Reading we will conclude the best wavelet transform. This methodology will remove noise and greater accuracy of result is obtained. The results are virtually simulated by using Matlab.

2.1. WAVELET PACKET DECOMPOSITION

Discrete wavelet transform splits the signal into two parts. That is multilevel decomposition. The first part which is low pass sub-band that is also known as approximation level. The second is high pass band which is also known as detail level [5]. The high pass filter has less noise and greater accuracy for analysis. So we can decompose the low pass filter into multiple level for fine analysis. Figure2.2 shows the Decomposition of wavelet in 5 Levels.

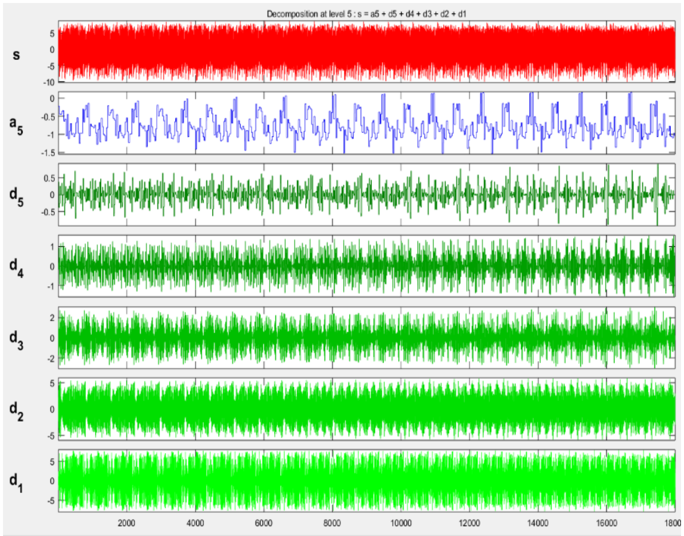

Fig-2.2: Wavelet decomposition of 5 Levels

We can use the same Input PPG signal to decompose the wavelet into level one to five. The fifth level shows the detailed coefficient of the signal. First level decomposition will give the high frequency details of the signal. The high frequency signal is often containing noise in it. These high frequency noise is comprising of abrupt change in the input signal. We want to retain these abrupt changes when providing the information of denoised signal

2.3. FILTERING

Filters are used in wide range of applications which includes video and audio signal processing, Echo Cancellation, noise cancellation and Adaptive Beamforming [7]. The noise interference will cause damage to the quality of the signal. To reduce unwanted noise in the signal filters were used. There are two types of filters used here they are adaptive filter and Savitzky-Golay filter. Here we are using adaptive filter. Figure2.3 represents the block diagram of adaptive filter.

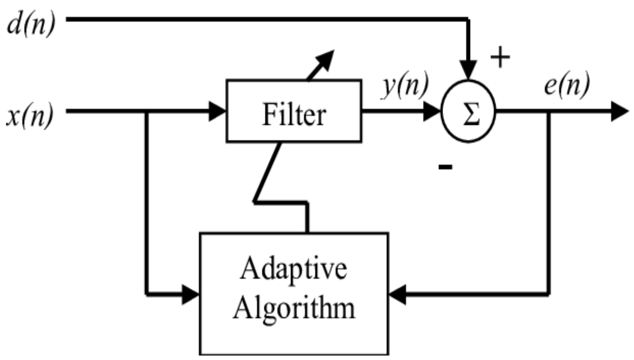

Fig-2.3: Block diagram of Adaptive filter

Original signal is denoted as d(n) and the noise signal is represented as s(n). Adaptive filter alters the parameter to get the desired noise which differentiate between d(n) and s(n). On each repetition of the error signal e(n) measures the difference between the original and noise signal and when the original signal matches with the desired signal then the error value becomes zero. Mathematical equation given is by

$s(n + 1) = s(n) + 2\,\mu\, e(n)\, d(n)$

Where d(n) is original signal and e(n) is error and μ is the step size

2.4. THRESHOLDING

The thresholding is done when the wavelet coefficient and noise level is of the same level, then the signal and the noise cannot be separated [8].

Thresholding can be done in two types

1) Soft Thresholding
2) Hard Thresholding

2.4.1. SOFT THRESHOLDING

In soft thresholding, coefficient less then threshold is set to zero and the coefficient that have greater magnitude then the threshold is shrunken towards the zero. So this soft thresholding is also called as wavelet shrinkage.

2.4.2. HARD THRESHOLDING

In hard thresholding coefficient less then threshold is set to zero and the coefficient greater in magnitude have no change ie, it lies above the threshold level.

2.5. THRESHODING METHODS

There are four types of thresholding method helpful for suppressing the wavelet coefficients and to recollect the data without noise. They are Rigrsure, Sqrtwology, Heursure, Minimaxi

2.5.1. RIGRSURE

Rigrsure is the stein impartial risk estimator, it is an impartial estimator of the mean square error of a nonlinear estimator which gives an indication of the accurateness of estimator. It is adaptive thresholding method. The equation is given by

$$\boldsymbol{\lambda = \sigma\sqrt{w_b}}$$

Where w_b is the coefficient of minimum risk and σ is the noise signal's standard deviation

2.5.2. SQRTWOLOGY

Threshold values which are calculated by using the square root log or universal threshold which usages static form of threshold value. Sqrtwology can be also called as global thresholding or ficed thresholding. Sqrtwology equation is given by

$$t_h = \sqrt{2\log(d_j)}$$

Where d_j is the coefficient of number of wavelets

2.5.3. HEURSURE

Heursure is the combination of Sqrtwology and Rigrsure. When the Rigrsure threshold is less it effects on the Heursure, it means that the signal to noise ratio is very less in that state. Sqtwolog threshold gives the best result when compared with other two thresholding.

2.5.4. MINIMAXI

Minimaxi threshold detection reading is best when the thresholding value is in the worst case. It satisfies the Baye's estimator criterion which reduces the loss function. The minimax thresholding is almost same as like sqrtwology thresholding and it will reduce the performance of the required signal against the Mean square error.

2.6. WAVELET TRANSFORM

Signals frequently occurring a changes in frequency and time transients. In capturing an images, they exhibit abrupt changes by interrupted in edges and other factor. These abrupt changes cause a defect in the image, changes in contrast etc. Fourier transform will not able to indicate the abrupt changes effectively. This is because the fourier transform exhibits in sin waveform. It will be oscillating to an infinite time period. So this brings into the concept of wavelet transform. There are two concepts in wavelet transform that is scaling and shifting. Scaling is the process of stretching and shrinking the signal by the equation $\Psi(t\ /\ f)s > 0$. Where s is scaling factor. Scaling factor is independent of frequency and dependent on time. Shifting means moving the onset of wavelet along the length. Its notation is $\emptyset(t-k)$ [3]. Wavelet transform have finite number of distance and can occur in any form. So it has the capability of analysing the frequency and time simultaneously.

2.7. DISCRETE WAVELET TRANSFORM

If the wavelets are discretely sampled, then it is called discrete wavelet transform. When compared to other wavelet discrete wavelet has captures both location and frequency information. It has dyadic shifting and scaling function. So it reduces redundancy in coefficients. Discrete wavelets always occupy less memory space. Discrete wavelet transform consists of two multilevel filter banks. When the signal is passed it decompose the signal into low pass filter and high pass filter. The samples got discarded into half of its original. As the samples got reduced it have good level of performance. Again the process is repeated as the low pass filter will get further separated into low pass and high pass filter. So the length of the coefficient got reduce into half in each stages and it will be easy for the analyzation of the signal. Discrete wavelet transform can be used in the application of denoising and the compression of images with the help of fewer coefficients.

2.7.1. HARR WAVELET

Haar wavelet is the simple and oldest wavelet type. Haar transform gives the architect for all the other wavelet transforms. The main advantages of harr wavelet are it provides fastest output, simple and memory effective. Haar wavelet decays the signal into two sub level signals. One signal provides the average and another signal provides the difference. It is not continuous so it is not differentiable and look like the step function.

The equation of Haar wavelet is

$$\psi(t) = \begin{cases} 1 & 0 \le t \le \frac{1}{2} \\ -1 & \frac{1}{2} \le t \le 1 \\ 0 & \text{otherwise} \end{cases}$$

Scaling function ϕ (t) can br defined as

$$\phi(t) = \begin{cases} 1 & 0 \le t \le 1 \\ 0 & \text{otherwise} \end{cases}$$

2.7.2. COIFLET WAVELET

It is a type of discrete wavelet function. Coiflet wavelet was found by Ingrid Daubechies in association with Ronald coifman to obtain functions for resizing the moments of escape. Coiflet wavelet is a type of symmetrical wavelet function. They have escape moments of $\frac{N}{3}$ and scaling function of $\frac{N}{3-1}$. Coiflet have two vanishing moments in which wavelet transform is high pass filter and scaling function is low pass filter. It will be normalized by $\frac{1}{\sqrt{2}}$ factor [2]. Coiflet wavelet is used in the application of calderon zygmund.

Its equation is given by

F = coifwavf(W)

Where F is the scaling filter function associated with Coiflet wavelet

Where W = 'coifN' and N is number of occurrences

There are 5 levels of Coiflet wavelet function. Figure2.7.1 shows the 5 stages of Coiflet in graphical format.

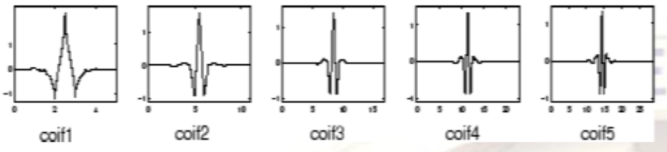

Fig-2.7.1: Levels of Coiflet wavelet

2.7.3. DAUBECHIES WAVELET

It is a discrete wavelet transform and it belongs to the family of orthogonal transform. It has the maximum number of vanishing moments. It can be mainly used for the decomposition of signal in time-frequency scale. It has balanced frequency response but it has nonlinear phase function. It has high frequency coefficient spectrum as it uses overlapping windows so in result it gives high frequency changes. So Daubechies can be useful to solve problems like signal discontinuity and factual difficulties [1].

Its equation is given by

$$C_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$$

Where C_i is the Daubechies function

i is the index of iteration

g is wavelet function coefficient and s is scaling function

There are 10 levels in Daubechies wavelet transform. Figure2.7.2 shows the pictorial representation of 10 stages of Daubechies wavelet.

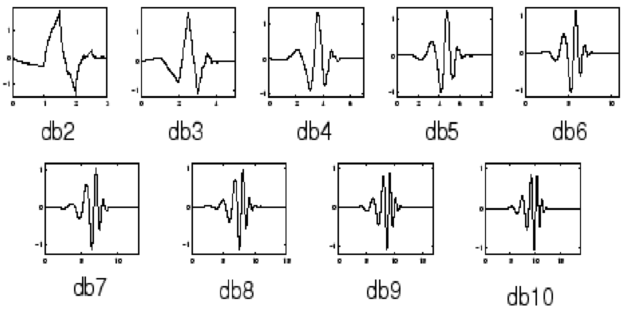

Fig-2.7.2: Levels of Daubechies wavelet

3. RESULT & DISCUSSION

The results are implemented by using Matlab. The input PPG signals are fed into Matlab. Then wavelet analyzer is opened then the PPG signals are imported in wavelet toolbox [9]. The Imported signals are decomposed into different level of the user needs. Here we are decomposing the signals into 5 levels for better analysis. Figure3.1 shows the decomposition of the original PPG signal into 5 levels.

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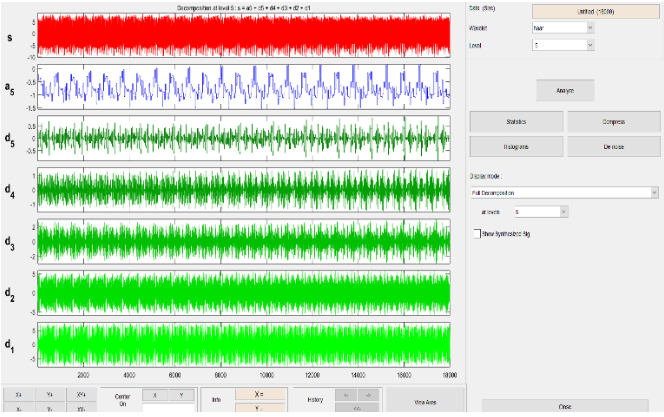

Fig-3.1: Decomposition of original PPG signal

Then the statistics of the input signal is opened to get the readings of the entire input PPG signal. Figure3.2 shows the statistics of the input waveform

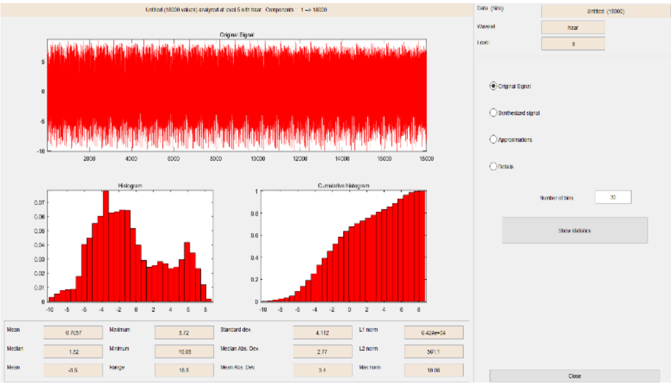

Fig-3.2: Statistics of the input signal

Statistics shows the all properties of input signal Mean, median, mode, Range etc. Each of the properties is tabulated. The tabulation comprises of the real time reading of the 10patient which is obtained by the implemented method. Each patient has 8set of separated reading to get the better accuracy of result during denoising. All the 8 set of reading is imported in Matlab and the mean of every 8 set of patient is acquired and then tabulated. Table1 shows the Sample features extracted from Input PPG dataset

MEAN

The mean can be derived as the sum of all the occurrence divided by the total number of occurrence

$$Mean = \frac{1}{n}\sum_{i=1}^{n} x_i$$

MEDIAN

The values are arranged in ascending or descending order and the middle value is taken as mean

$$Median = \frac{n+1}{2}$$

MODE

Mode is the value which have high number of occurrence in the given set

MINIMUM

Minimum denotes the lowest value observed among the input value

$$Minimum = x_i \rightarrow min(x_i)$$

MAXIMUM

Maximum denotes the highest value observed among the input value

$$Maximum = x_i \rightarrow max(x_i)$$

RANGE

Range is the value obtained from the difference between highest and lowest value that occurred in a set

$$\text{Range} = \max(x_i) - \min(x_i)$$

Input PPG	Mean	Median	Mode	Max	Min	Range
Patient - 1	-0.1241	-0.72	5.82	10.24	-10.16	20.4
Patient - 2	-0.252	-0.69	-7.1	10.84	-10.29	19.7
Patient - 3	-1.442	-1.28	-0.3	10.73	-10.96	19.9
Patient - 4	-0.7657	-1.52	-3.5	8.72	-10.08	18.8
Patient - 5	-0.1365	-0.48	-4.459	10.08	-8.48	18.56
Patient - 6	-1.03	-2.16	-3.7	10.24	-10.16	20.4
Patient - 7	0.9606	1.2	2.92	9.92	-10.08	20
Patient - 8	-0.2086	-0.69	-4.64	10.24	-9.6	19.84
Patient - 9	0.4588	0.43	0.2075	8.69	-10.16	18.85
Patient - 10	-2.46	-4.48	-7.067	7.6	-8.4	16

Table -1: Sample features extracted from Input PPG dataset

Next the 10 set of patients is Denoised on basis of Haar wavelet transform. The thresholding method is fixed and soft thresholding is applied here. By denoising through this method the noise is eliminated from the input PPG signal. Figure3.3 shows the denoised image of image PPG signal using Haar wavelet transform.

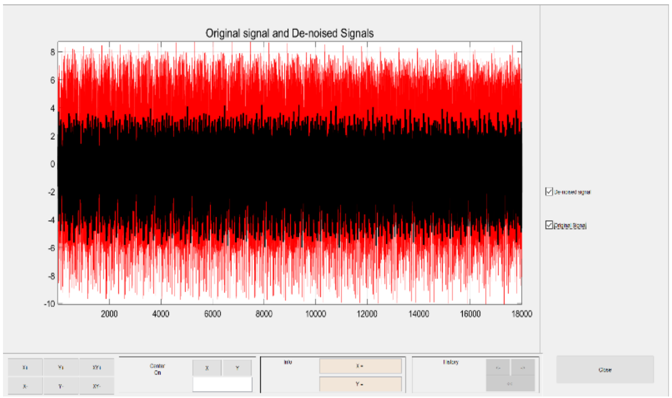

Fig-3.3: Denoised PPG signal using Haar wavelet

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Here the Red colored portions indicated the original PPG signal with noise and the black colored portion indicates the denoised signal by means of Haar wavelet transform

Then the statistics of the PPG signal which is denoised by using Haar wavelet transform is obtained. Table2 shows the Sample features extracted from the denoised Haar wavelet transform.

Haar Denoised	Mean	Median	Mode	Max	Min	Range
Patient - 1	-0.1241	-0.1584	-0.335	7.078	-7.271	14.35
Patient - 2	-0.252	-0.4436	-2.016	7.985	-8.232	16.22
Patient - 3	-1.442	-1.452	-1.317	4.856	-7.915	12.77
Patient - 4	-0.7657	-0.8798	-1.083	4.195	-6.021	10.22
Patient - 5	-0.1365	-0.1581	-0.147	5.035	-4.996	10.03
Patient - 6	-1.03	-1.16	-1.264	5.586	-7.672	13.26
Patient - 7	0.9606	0.9828	1.063	5.163	-3.32	8.483
Patient - 8	-0.2086	-0.2178	-0.365	5.431	-5.107	10.54
Patient - 9	0.4588	0.4756	0.5445	4.759	-5.355	10.11
Patient - 10	-2.46	-2.785	-2.934	2.295	-6.669	8.964

Table-2: Sample features extracted from Denoised haar wavelet

For better analysis the denoised image can be viewed on the histogram of the wavelet analyzer. Figure3.4 shows the histogram graph PPG signal denoised by using Haar wavelet transform. Red colour bar graph is the histogram of original PPG signal and the violet coloured bar graph is the denoised portion using haar wavelet. From that image we can observe the comparison graph of input and denoised signal.

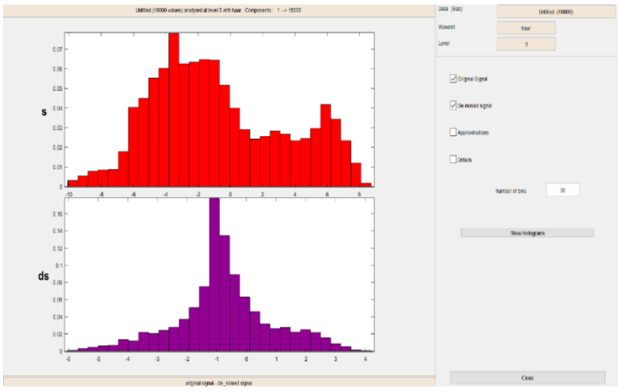

Fig-3.4: Histogram of Haar wavelet

Similarly, the values of denoising using Daubechies wavelet transform is obtained by following the same procedure. Here the Daubechies is denoised in 4^{th} stage by soft thresholding and fixed thresholding method. Table3 shows the Sample features extracted from the denoised Daubechies wavelet transform.

Db4 Denoised	Mean	Median	Mode	Max	Min	Range
Patient - 1	-0.1248	-0.1629	-0.134	8.411	-7.127	15.54
Patient – 2	-0.2529	-0.3481	0.0331	8.515	-9.034	18.55
Patient - 3	-1.443	-1.46	-1.178	6.852	-7.747	15.6
Patient - 4	-0.7663	-0.7555	-0.0854	3.74	-6.24	10.98
Patient - 5	-0.1358	-0.1539	-0.215	4.805	-4.323	10.128
Patient - 6	-1.03	-1.192	-1.058	5.5856	-8.449	15.31
Patient - 7	0.9611	0.9502	0.8323	5.868	-4.551	11.42
Patient - 8	-0.2088	-0.2224	-0.261	4.905	-5.094	10.99
Patient - 9	0.4594	0.4932	0.5304	5.278	-4.545	10.823
Patient - 10	-2.46	-2.776	-2.646	3.119	-7.363	11.48

Table-3: Sample features extracted from Denoised Daubechies(Db4) wavelet

Similarly, the values of denoising using Coiflet wavelet transform is obtained by following the same procedure. Here the Coiflet wavelet is denoised by 2^{nd} stage and fixed thresholding method. The second stage of Coiflet denoising is used as it gives the best accuracy of results. Soft thresholding is applied for denoising of all wavelet transform methods. Table4 shows the values obtained for denoising by means of Coiflet wavelet transform.

Coiflet Denoised	Mean	Median	Mode	Max	Min	Range
Patient - 1	-0.124	-0.1695	-0.3344	8.238	-5.663	13.9
Patient - 2	-0.252	-0.3645	0.0495	9.252	-8.559	17.81
Patient - 3	-1.442	-1.453	-1.291	5.582	-7.915	13.5
Patient - 4	-0.765	-0.8637	-0.8139	4.41	-5.701	10.11
Patient - 5	-0.1364	-0.1605	-0.125	4.0389	-4.02	8.059
Patient - 6	-1.03	-1.398	-1.637	5.921	-7.035	12.96
Patient - 7	0.9606	0.9579	0.841	5.571	-4.215	9.785
Patient - 8	-0.2085	-0.2893	-0.096	5.735	-4.874	10.61
Patient - 9	0.4593	0.4718	0.5997	4.977	-4.079	9.055
Patient - 10	-2.46	-2.872	-3.18	3.768	-6.921	10.69

Table-4: Sample features extracted from Denoised Coiflet wavelet

By comparing all the 4 tables we can conclude which denoising is best suitable for PPG signal. In table1 input PPG signal values is given. It is compared with each other tables and every category of the values are analyzed. By comparing all the factors Daubechies(Db4) have greater range of Denoising the input PPG signal. The values of Mean, Median, Mode also in Daubechies wavelet have better accuracy of denoising when compared with other two wavelets.

Figure3.5 shows the detailed output image of the PPG signal denoised by using the Daubechies wavelet transform.

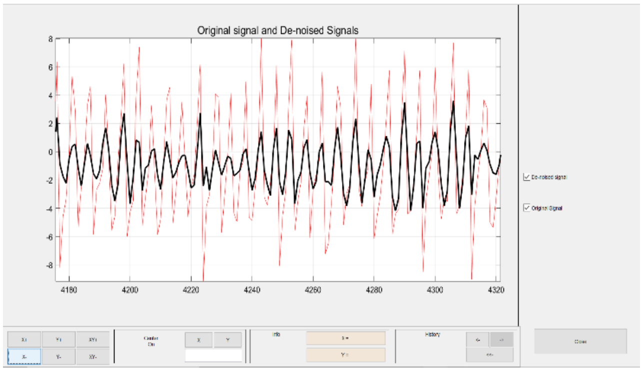

Fig-3.5: Denoised output of Daubechies wavelet

In the figure red coloured line indicates the original signal before denoising and the black coloured line indicates the denoised signal by using Daubechies wavelet. From this the Daubechies(Db4) have greater accuracy of denoising. So for denoising of any PPG signal Daubechies wavelet can be implemented. The results can be visually presented in real-time using Matlab.

4. CONCLUSION AND FUTURE SCOPE

This paper has discussed about PPG signal and its denoising. First we came to know how PPG signals are measured and its working. That measured PPG signal is affected by noise. So to reduce noise we have discussed about the denoising and its implementation methods. The data are collected from the capnobase and implemented in real-time using Matlab. After that the types of denoising methods using wavelet transform was discussed. This paper has brought the unique solution of about which wavelet transform is best suitable for denoising of PPG signals. From the results we conclude that the Daubechies wavelet transform has better accuracy of denoising when compared with other wavelet transforms. So these can be useful for the physicians for measuring the heartbeat using photoplethysmography method. Also it will be useful for public for preventing themselves from heart related issues.

In near future the artificial intelligence techniques to be used for the performance analysis and classification of PPG signals of different datasets.

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