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Classification of PPG Arrhythmias using Discrete Wavelet Feature Extraction and Artificial Neural Networks

Jayadevappa B.M[1], Mallikarjun S. Holi[2]

Professor, Department of Electronics and Instrumentation Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[1]

Professor, Department of Studies in Electronics and Instrumentation Engineering, University B.D.T. College of Engineering, Visvesvaraya Technological University, Davangere, Karnataka, India[2]

Abstract: PPG signal is an effective method to assess the cardiovascular parameters like heart rate, blood oxygen saturation, blood pressure and respiration rate. Motion and other artifacts introduced during acquisition of PPG, limits the accuracy in estimation of clinical parameters. In this paper, we present wavelet based feature extraction and motion artifacts removal methodology to overcome the issues of heart and respiratory parameter estimation. In the proposed algorithm, point of interest coefficients are ascertained for every wavelet sub-band grid, producing a changed wavelet sub-band network. This makes the exhibited algorithm more efficient. Every information set comprises of deliberately made conceivable MA noises, viz., vertical, flat, waving, and squeezing MAs with distinctive breathing examples. The technique is connected on the recordings accessible of Physionet dataset. The measurable and classification investigation, performed to test the viability of the introduced new algorithm, uncovered a decent acknowledgment for inferred respiratory signal, when contrasted and the initially recorded respiratory signals utilizing traditional strategy. To perform the classification of the dataset, neural network is used. The proposed strategy obviously outperforms the customary heart rate detection system in the vicinity of MA. The results of proposed system show the approximate 99.9% of sensitivity and 99.7% of specificity.

Keywords: PPG, Heart rate, Respiration rate, classification, neural network.

I. INTRODUCTION

Photoplethysmography is a system utilized for measuring the blood volume changes in an organ optically. PPG signal can be utilized as a pointer of the heart movement. It can be seen that the top of the PPG signal matches with the R crest of the ECG signal [1]. Also, it can be utilized to recognize a few organic issues like blood vessel checks, heart illnesses and so forth. There are two distinct techniques for getting PPG waveforms: transmission PPG and reflection PPG [2]. In transmission sort, light is transmitted into the tissue and a light detector is set in the other side of the tissue to gauge the transmitted light. However in the reflection sort, the light source and the light detector are both set on the same side of a body part. At that point the reflected light is measured by the identifier. The most well-known clamor sources connected with PPG are the surrounding light, electromagnetic coupling from other electronic instruments and other movement aggravations. Among the extensive variety of clamor sources meddling with the PPG signal, the movement ancient rarities created by the quiet's development is exceptionally hard to uproot. Additionally the vicinity of electrical cable impedance is a noticeable commotion in PPG [3].

The work presented concentrates on the evacuation of motion artifact from the ruined PPG signal which empowers to translate the signal all the more effectively and precisely. Different methodologies are utilized to alter and process movement tainted estimations. The primary technique that was utilized for evacuation of MA was Fourier arrangement. Since PPG being a semi intermittent and non-stationary signal it is impractical to utilize Fourier arrangement straightforwardly [4]. Intermittent moving normal channel which looks into the semi periodicity of the PPG signal was later presented [4]. This strategy functions admirably for the evacuation of discontinuous clamor, yet can't uproot the MA of substantial abundance or one that happens all of a sudden. Later it is found that wavelet can be utilized for the evacuation of MA in PPG signal [5]. In this Gaussian commotion included with the PPG is uprooted utilizing diverse mother wavelets. It can be seen that Daubechies (db4) wavelet capacities indicates much proficient result contrasted with different wavelets. The use of Independent Component Analysis (ICA) portrayed in [6] demonstrates that the movement ancient rarities can be diminished by misusing the semi periodicity of the PPG signal and the autonomy between the PPG and the movement antiquity signals. This technique makes utilization of a pre-processor and ICA. Since it doesn't require earlier information of the framework it is exceptionally valuable for MA evacuation yet its inconvenience is that it considers that all source signal segment sets as commonly free. Singular Value Decomposition (SVD) is a numerical device that can be utilized for the evacuation of MA in PPG signal [7]. Multi-Scale Principal Component Analysis (MSPCA) makes utilization of the de-relationship capacity of Principal Component Analysis (PCA). It can be seen that the MSPCA performs superior to anything fundamental wavelet handling. Versatile channels can likewise be utilized for the evacuation of MA influenced PPG signal [8]. This strategy makes utilization of a manufactured reference signal for versatile separating reason. This reference signal is created from data of PPG signal itself. It can be seen that utilizing Fixed-interim Kalman channel alongside versatile channel gives preferred result over versatile channel utilized alone. During all these researches, removing motion artifact from PPG signal is the most challenging task. This motion induces the noise which affects the analyzing quality of signal [9]. Heart rate variability (HRV) is a measure of a vacillation of time interim between heart beats. HRV is computed considering electrocardiogram (ECG) signals, blood vessel pulse signals or photoplethysmography (PPG) signals inferred time arrangement of in the middle of heart pulsates [10].

Although the solutions provided in previous works are adequate methods for identifying high quality data segments, during arrhythmias, heart rate detection and blood pressure measurement. But these approaches are not satisfactory for the signal which contains low quality, so these approaches require larger window size to analyze each beat. Additionally, resolution of the PPG signal is more challenging task for heart rate calculation. Due to these issues it is difficult to determine the normal and abnormal heart rate of the patient.

In this work we propose wavelet based feature extraction algorithm to analyze the feature of normal and abnormal heart rate of the patient. These features are analysed statically in further sections. Finally, artificial neural network based framework is proposed for the classification of normal and abnormal heart rate.

The other sections of the presented manuscript discuss, related work in Section II, Section III presents the proposed model, which is followed by results and discussion in Section IV. The conclusion of the presented work is given in Section V and the references used throughout manuscript are given at the last of the paper.

II. RELATED WORK

In this section we present recent researches which have been proposed by researchers to bridge the gap between motion artifact removal and heart rate monitoring. Automatic patient observing is a vital asset in clinics for a decent medicinal services administration. While alerts because of anomalous physiological conditions are imperative to convey quick treatment, it can be likewise a wellspring of pointless commotion because of false cautions brought about by electromagnetic impedance or movement curios. This condition prompts anxiety, rest issue in patients and desensitization in staff. The huge sources of false cautions are those identified with heart rate, which is activated when the heart cadence of the patient is too quick or too moderate. Different sorts of heart arrhythmia alerts likewise depends on a decent recognition of the HR.

With a specific end goal to stay away from false cautions, it is vital to make frameworks for dependable heart rate figuring. Nitzan, M.; Dayan et.al. [11], discussed that the breath prompts variances in heart rate and blood vessel circulatory strain, starting from either mechanical impact of breath or from changes in autonomic sensory system movement. Keeping in mind the end goal to ponder the relationship between cardiovascular hemodynamics and the two periods of breath, motivation and lapse, they utilized the PPG signal, which mirrors the heart actuated changes in the tissue blood volume.

In order to estimate the reliable heart rate, Bayesian fusion algorithm is proposed in [12]. For validation of the proposed work, white noise was added to the original signal and compared with other methods. Mouradian, V.; Poghosyan et.al. Proposed a novel PPG optical sensor and gadget with encompassing optical, electrical and electromagnetic clamors cancelation, in this manner permitting just the valuable optical signals to be gotten by the health observing gadget [3]. The introduced sensor and system has been coordinated into a model standalone gadget for non-invasive, ceaseless, wearable, remote and versatile checking of pulse and other human indispensable also, for example, heart rate, oxygen immersion, breath rate, and so forth.

Non-invasive continuous circulatory strain checking is not yet basically accessible for day by day utilization. Difficulties incorporate making the framework effectively wearable, lessening clamor level and enhancing exactness. Varieties in every individual’s physical qualities, and in addition the likelihood of distinctive stances, expand the unpredictability of persistent BP checking, particularly outside the healing facility. This work endeavors to give an effortlessly wearable arrangement and proposes preparing to particular stance and individual for further enhancing exactness. The wrist watch based framework Thomas, S.; Nathan created can quantify ECG and PPG. From these two signals he measured heartbeat travel time which is called as pulse transit time (PTT) through which we can get systolic and diastolic pulse through relapse strategies. In this work, Thomas, S.; Nathan examined different capacities to perform the preparation to get circulatory strain [13].

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III. PROPOSED METHODOLOGY

In this section we present the proposed model and methodology in order to achieve the better classification results as well as robust method for heart rate detection. Overall architecture and working of the proposed system is described below.

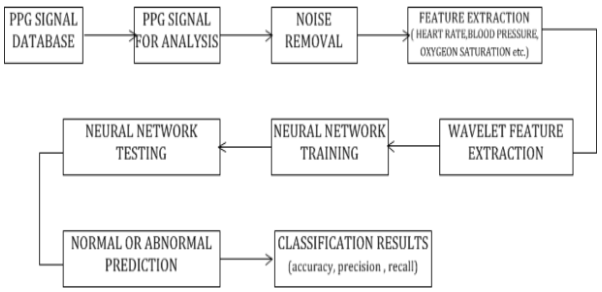

Fig.1 Proposed system architecture

Fig.1 presents the overall architecture of the proposed model. First step is to collect the various PPG signal datasets with varied parameters. Next step is to select the collected signals for further processing. If these signal contains any noise which can be removed by normal pre-processing stage i.e. step 3, otherwise wavelet transform is used for removing the noise. Next step is to extract the features i.e. heart rate, blood pressure and oxygen saturation etc. After extraction of these features we extract wavelet features by using discrete wavelet transform method. Finally these feature extracted data is given to the artificial neural network to perform the training and testing on the dataset in order to achieve the predicted classes which are defined as normal patient and abnormal patient. After getting these results, validation of proposed system is done by calculating accuracy and precision of the proposed system and recall of the proposed system. The key point of is to perform noise removal by using wavelet transform and feature extraction and are discussed below.

A. Wavelet Transform: Noise Removal

Wavelet is utilized for minimizing the commotion. After wavelet deterioration, the high recurrence sub groups contain a large portion of the commotion and low frequency sub groups the greater part of the signal data. Commotion produced by movement antiquities is basically minimized by disintegrating the PPG signals into an arrangement of wavelet sub groups. The peaks are distinguished utilizing some limit estimation of the recreated signal. Wavelet transform is idea of applying convolution of the signal with a short wave which is moved from the beginning to end of the signal, the short wave, called wavelet. This is a reason for opening up a specific recurrence in view of the scale it employments. As the scale changes, the wavelet change accentuates diverse frequencies in the signal. There are two sorts of wavelet change continuous and discrete wavelet changes [14]. The mathematical representation of continuous wavelet transform is defined as

$$\mathbb{X}_{wc}(a,b) = \frac{1}{\sqrt{a}}\int_{-\beta}^{\beta} \mathbb{X}(t)\chi * \left(\frac{t-b}{a}\right)dt \qquad \text{Eq. (1)}$$

Where, $\mathbb{X}_{wc}$ is the continuous wavelet transform of $\mathbb{X}(t)$, and χ is the child wavelet.

Discrete wavelet transform (DWT) is utilized for this investigation because of the fact that it gives adequate data to examination and combination of the first signal with less computational time [15]. In DWT the signal is gone through a progression of high pass channels and through a progression of low pass channels to break down the high frequencies and low frequencies individually. The signal's determination which is a measure of amount of point of interest data of the signal is changed by sifting operation. The recurrence scale is changed by up-sampling and down-sampling. The natural discrete signal x[n] is gone through half band high pass h[n] and low pass l[n] channels making two sub-bands both inspected at half of the first recurrence. These channels estimated half-band Finite Impulse response (FIR) channels that are dictated by the decision of wavelet. The transfer speed of every channel yield and sub-band is a small amount of examining recurrence equivalent to the Nyquist rate of half of the examples can be dispensed with. One level of decay is communicated by

$$y_h[k] = \sum_n x[n]h[2k-n] \qquad \text{Eq. (2)}$$

$$y_l[k] = \sum_n x[n]l[2k-n] \qquad \text{Eq. (3)}$$

Where 'l' term indicates the low pass channel yield and 'h' term means the high pass channel yield [15]. This deterioration is reapplied to the low sub-band yield over and again which has the impact of multiplying the recurrence determination band diminishing the time resolution by the variable of two since a large portion of the quantity of tests now makes up the signal. This sub-band coding method is rehashed for various levels of deterioration and each decay results down the middle the quantity of tests and along these lines diminishing the time determination by a component of 2 and taking a large portion of the recurrence band there by multiplying the recurrence determination. Just perfect half band channel, for example, different wavelet channel banks permit the ideal reproduction of the first flag.

B. Wavelet Transform: Feature Extraction

In the feature extraction step, various distinctive techniques can be utilized so that few differing elements can be extricated from the same crude information. The wavelet transform (WT) gives extremely broad methods which can be connected to numerous errands in signal preparing. Wavelets are in a perfect world suited for the examination of sudden brief length of time signal changes. One imperative application is the capacity to register and control information in compacted parameters which are

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frequently called highlights [16]. Subsequently, the time-shifting biomedical signal, comprising of numerous information focuses, can be packed into a couple of parameters by the utilization of the WT. These parameters describe the time's conduct differing biomedical signal. This element of utilizing a fewer number of parameters to speak to the time-changing biomedical signal is especially critical for acknowledgment and symptomatic purposes. The present's target study in the field of computerized identification of changes in time-fluctuating biomedical signals to separate the agent components of the signals under study so as to get the precise grouping models. Persistent, in the connection of the WT, suggests that the scaling and interpretation parameters change ceaselessly. On the other hand, computing wavelet coefficients for every conceivable scale can present an extensive exertion and result in a boundless measure of information. Consequently discrete wavelet change (DWT) is frequently utilized. The WT can be considered as an augmentation of the excellent Fourier transform, aside from that, rather than chipping away at a solitary scale (time or recurrence), it takes a shot at a multi-scale premise. This multi-scale highlight of the WT permits the decay of a signal into various scales, every scale presents to a specific coarseness of the signal under study. The technique of multi-resolution deterioration of a signal x[n] is schematically appeared in Fig. 2. Every phase of this plan comprises of two computerized channels and two down-samplers by 2. The principal channel, g [·] is the discrete mother wavelet, high-pass in nature, and the second, h [·] is its mirror form, low-pass in nature. The down-sampled yields of first high-pass and low-pass channels give the subtle element, D1 and the estimation, A1, individually. The main estimation, A1 is further decayed and this procedure is proceeded as appeared in Fig. 2

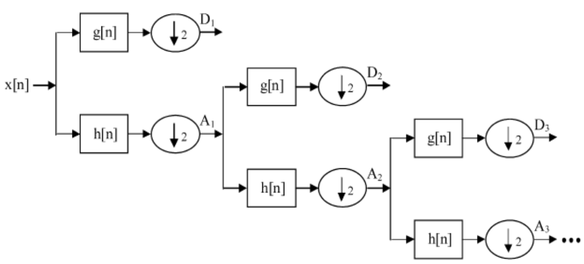

Fig. 2 Decomposition of signal

Wavelet transforms can be presented with the help of low pass filters. By representing wavelet transform with the help of low pass filter quadrature condition of filtering can be achieved which is defined as below:

$$\mathcal{H}(\mathcal{Z})\mathcal{H}(\mathcal{Z}^{-1}) + \mathcal{H}(-\mathcal{Z})\,\mathcal{H}(-\mathcal{Z}^{-1}) = 1 \qquad \text{Eq. (4)}$$

$\mathcal{H}(\mathcal{Z})$, Represents the z-transform of the h filter which can be achieved by equation 2 and equation 3.
High pass filter is defined as

$$\mathcal{G}(\mathcal{Z}) = \mathcal{Z}\,\mathcal{H}(-\mathcal{Z}^{-1}) \qquad \text{Eq. (5)}$$

Sequence of filter is defined for low-pass is given by equation 6 and for high-pass is given in equation 7

$$\mathcal{H}_{n+1}(\mathcal{Z}) = \mathcal{H}(\mathcal{Z}^{2n})\mathcal{H}_n(\mathcal{Z}), n = 0, \ldots., n \qquad \text{Eq. (6)}$$

$$\mathcal{G}_{n+1}(\mathcal{Z}) = \mathcal{G}(\mathcal{Z}^{2n})\mathcal{H}_n(\mathcal{Z}), n = 0, \ldots., n \qquad \text{Eq. (7)}$$

In order to get the sequence of filter by using equation 6 and 7 initial condition is taken
$\mathcal{H}_0(\mathcal{Z}) = 1.$
From here time-domain expression is computed as
For low-pass filter is computed using equation 8

$$h_{n+1}(\mathcal{T}) = [h]_{\uparrow 2^n} * h_n(\mathcal{T}) \qquad \text{Eq. (8)}$$

For high-pass filter is computed using equation 9

$$g_{n+1}(\mathcal{T}) = [g]_{\uparrow 2^n} * h_n(\mathcal{T}) \qquad \text{Eq. (9)}$$

In the above equation $\uparrow 2^n$ represents the sampling factor, $\mathcal{T}$ represents the equal sampled time. To get the detailed coefficients the wavelets need to be normalized which can be computed using

$$\theta_{n,l}(\mathcal{T}) = 2^{\frac{n}{2}} h_n(\mathcal{T} - 2^n l) \qquad \text{Eq. (10)}$$

$$\omega_{n,l}(\mathcal{T}) = 2^{\frac{n}{2}} g_n(\mathcal{T} - 2^n l) \qquad \text{Eq. (11)}$$

Finally decomposition of wavelet can be defined as

$$\mathcal{A}_n(\ell) = x\left((\mathcal{T}) * \theta_{n,l}(\mathcal{T})\right) \qquad \text{Eq. (12)}$$

$\mathcal{A}$ is the approximation constant

$$\mathcal{D}_n(\ell) = x\left((\mathcal{T}) * \theta_{n,l}(\mathcal{T})\right) \qquad \text{Eq. (13)}$$

$\mathcal{D}$ Represents the detailed coefficients of wavelet transform
The determination of fitting wavelet and the quantity of disintegration levels is imperative in investigation of signals utilizing the WT. The quantity of decomposition levels is picked taking into account the overwhelming recurrence parts of the signal. The levels are picked such that those parts of the signal that connect well with the frequencies needed for order of the signal are held in the wavelet coefficients. In the present study, the quantity of decomposition levels was decided to be 4. Along these lines, the PPG signals were disintegrated into the subtle elements D1–D4 and one last estimation, A4. As a rule, tests are performed with distinctive sorts of wavelets and the one which gives most extreme effectiveness is chosen for the specific application. The smoothing component of the Daubechies wavelet of 2nd order (db2) made it more suitable to identify changes of the signals under study [15]. Along these lines, the wavelet coefficients were registered utilizing the db2 as a part of the present study. The feature determination is a critical part of planning the neural system taking into account design arrangement since even the best classifier will perform ineffectively if the components utilized as inputs are not chose well. The registered discrete wavelet coefficients give a smaller

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representation that demonstrates the vitality dissemination of the signal in time and recurrence. In this way, the processed discrete wavelet coefficients of the PPG signals of every record were utilized as the component vectors represents to the signals. So as to diminish the dimensionality of the separated component vectors, measurements over the wavelet's arrangement coefficients was utilized. The accompanying factual elements were utilized to speak to the time-recurrence conveyance of the signals under study:

1. Greatest of the wavelet coefficients in each sub-band.
2. Mean of the wavelet coefficients in each sub-band.
3. Least of the wavelet coefficients in each sub-band.
4. Standard deviation of the wavelet coefficients in each sub-band.

IV. NEURAL NETWORK

In order to classify the dataset we use neural network algorithm which is discussed in this section. Classification is achieved by dividing the data into training and testing sets. Feed –forward neural network algorithm is used to perform the training on the dataset.

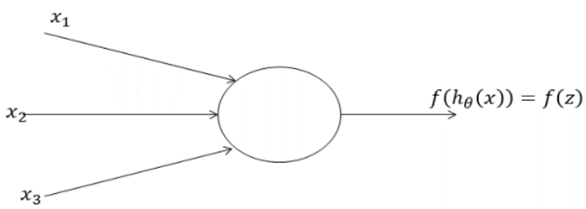

Fig. 3 Simple model of neural network

Neural network is used to define a complex non-linear data using input vectors and the weight parameters. Above given figure shows the simplest neural network. Computation is performed by neuron, according to which it takes the input as $\vec{x}$ and gives the output as f(θ_0 + θ1x1+ θ2x2=fhθx=fz

For this operation of classification it requires training set and testing set. In this work we use feed forward neural network along with the Levenberg Marquardt (LM) and the parameters used for neural network are mentioned in below given table1

Table 1. Configuration of ANN model

ANN Parameter	Considered Value
Hidden Layer	5
Learning Rate	50, 75,100 (in %)
Validation Ratio	50, 75,100 (in %)
Training Rate	50, 75,100 (in %)
Number of Epochs	1000
Target Class	2

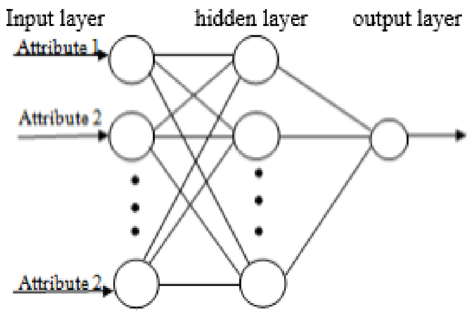

Fig.4 Architecture of neural network

Working of neural network:

- Randomly choose the initial weights, while error is too large
- For each training pattern (presented in random order)
- ➢ Apply the inputs to the network
- ➢ Calculate the output for every neuron through the hidden layer(s), to the output layer
- ➢ Calculate the error at the outputs
- ➢ Use the output error to compute error signals for pre-output layers
- ➢ -Use the error signals to compute weight adjustments
- ➢ -Apply the weight adjustments
- ➢ Periodically evaluate the network performance.

V. RESULTS AND DISCUSSION

In this section results and their discussion is presented. Initially we have considered raw signal and are processed by proposed algorithm. To analyse the PPG signal of all users we have computed minimum, maximum, mean and standard deviation and are as shown in Table 2.

Table 2. Statistical analysis of PPG signals

Subject	Min.	Max.	Mean	Std.	Normal(0)/Abnormal(1)
1	69.5876	165.6151	123.4003	45.7224	1
2	69.5160	148.5923	111.8944	38.1298	0
3	83.7054	160.4278	114.8730	74.8858	1
4	78.9474	164.0625	121.3863	43.7462	1
5	101.2373	166.8432	129.5117	44.1937	1
6	68.7285	153.0612	123.2809	39.7974	0
7	92.1187	157.5630	120.3115	45.8078	0

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8	74.5342	150.7937	125.1246	19.3871	0
9	74.2574	151.2739	117.4040	38.7727	0
10	121.3592	176.7418	149.4707	43.0941	1
11	110.0629	170.6392	136.2895	50.1667	1
12	96.8310	170.2786	129.2664	45.2997	1
13	69.5876	165.6151	123.4003	45.7224	1

According to the American Heart Association (AHA) we have classified the normality and abnormality of the heart rate. According to AHA resting heart rate is the number of times heart beats per minute while it's at rest. The average heart rate represented in the table 3 for age variation of the user. In figure 12, heart rate of all users is plotted. It can be measured from the table 3 that if heart rate of any user is exceeding 160 beats per minutes is considered abnormal heart rate which is denoted by 1 for the classification and if the heart rate of the user is less than 160 beats per minutes is considered normal heart rate denoted by 0.

Table 3. Age and heart rate for the subjects

Subject age in years	Heart Rate in beats per minute
20	100-170
30	95-162
35	93-157
40	90-153
45	88-149
50	85-145
55	83-140
60	80-136
65	78-132
70	75-128

Fig 5 and 6 shows the recorded raw PPG signals of normal and abnormal subjects.Fig.7 shows the filtered signal.Fig 8 and 9 shows the approximation and detailed coefficients of abnormal subjects.Fig 10 and 11 shows the approximation and detailed coefficients of normal subjects.

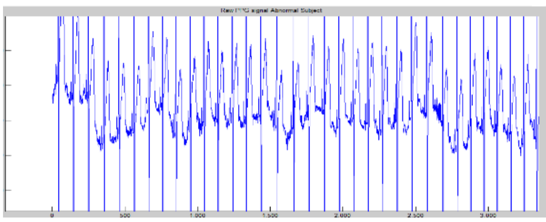
Fig. 5 Raw PPG signal of abnormal subject

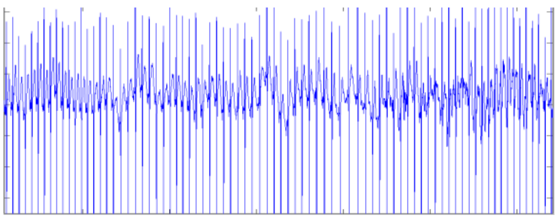
Fig. 6 Raw PPG signal of normal subject

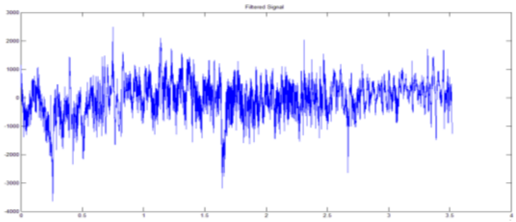
Fig.7 Filtered Signal

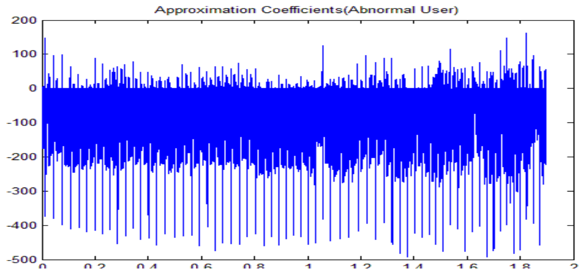

Fig. 8 Approximation Coefficients of abnormal subject

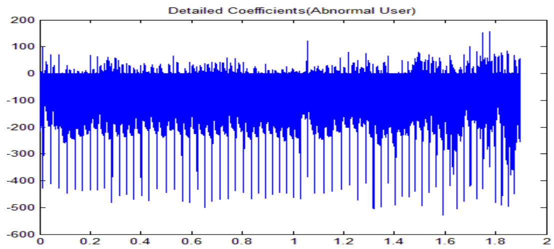

Fig. 9 Detailed Coefficients of abnormal subject

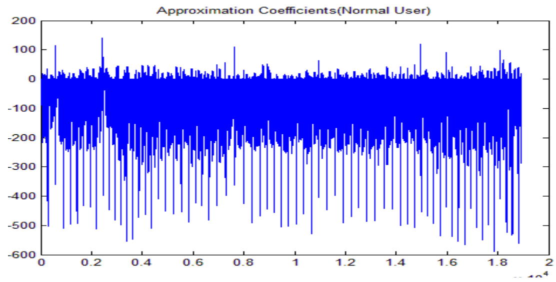

Fig. 10 Approximation Coefficients of normal subject

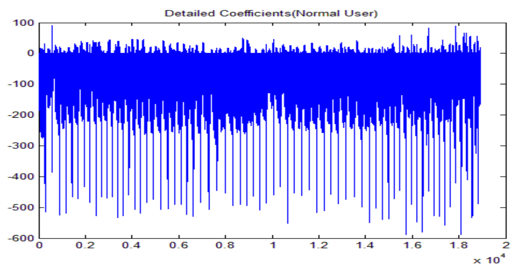

Fig. 11 Detailed Coefficients of normal subject

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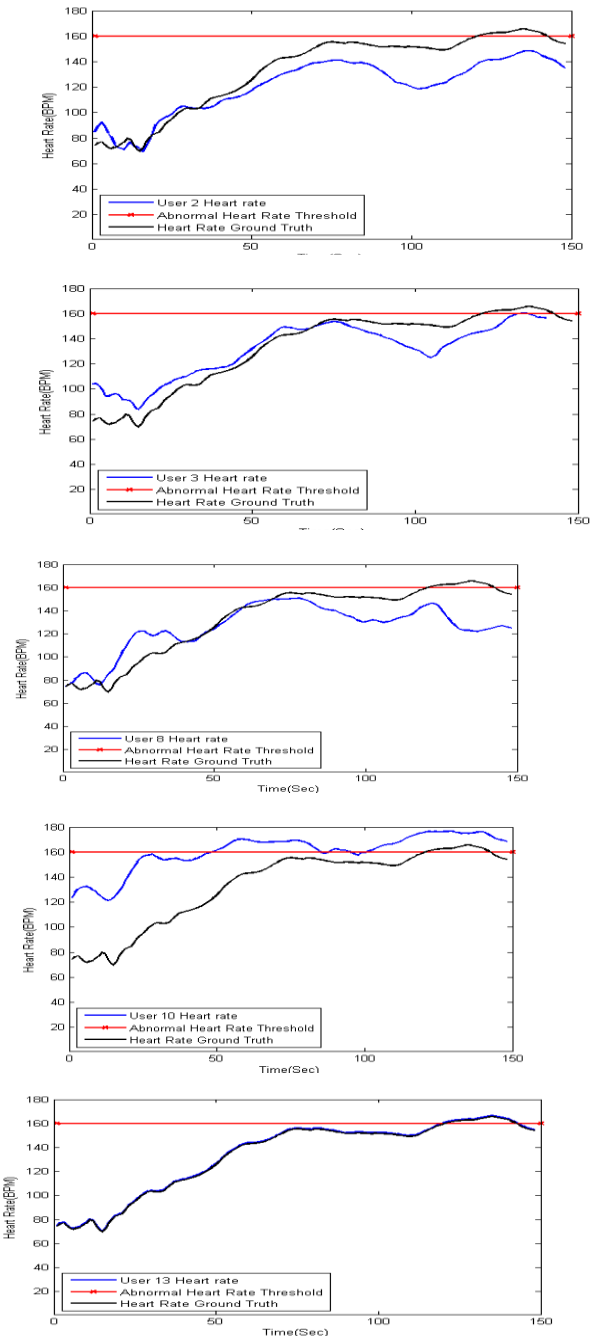

Fig.12 Heart rate plots

Fig.12 shows the heart rate plot of few subjects among 13 indicating the heart rate, abnormal heart rate threshold and heart rate ground truth plots. In the experiment we have taken PPG signal from 13 subjects to determine the normal and abnormal heart rate classification by using artificial neural network. According to American heart Association standards, in our Dataset 8 users are having abnormal heart rate and the remaining 5 are with normal heart rate. To perform the classification we have divided this data into two classes: normal class or normal heart rate and abnormal class or abnormal heart rate. Normal class is represented by 0 and abnormal class is by 1, which is tabulated in table 2.

Table 4 gives the maximum heart rate of each user.

Table 4 Heart rate

Subjects	Maximum Heart Rate
1	165.61
2	148.59
3	160.43
4	164.06
5	166.84
6	153.06
7	157.56
8	150.79
9	151.27
10	176.74
11	170.64
12	170.28
13	165.62

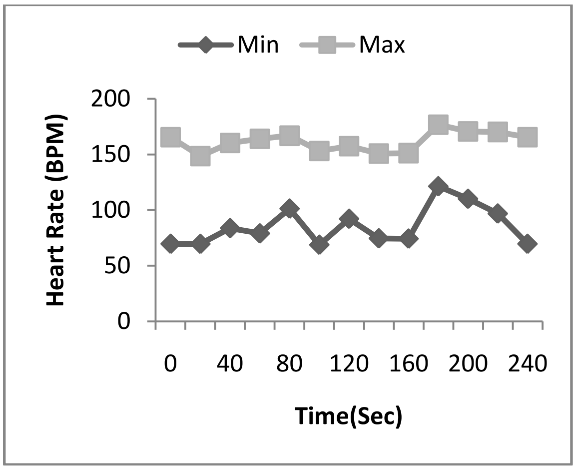

Fig.13 Minimum and maximum heart rate variation

The fig. 13 represents the minimum and maximum heart rate variation for all subjects of different age.

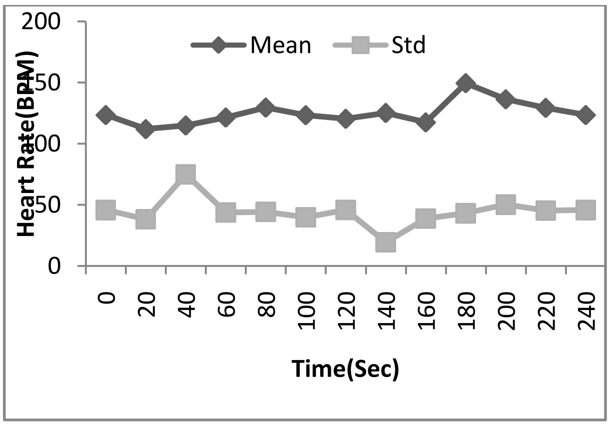

Fig.14 Mean and standard deviation of the PPG signal

The above given fig. 14 represents the mean and standard deviation of heart rate for all subjects.

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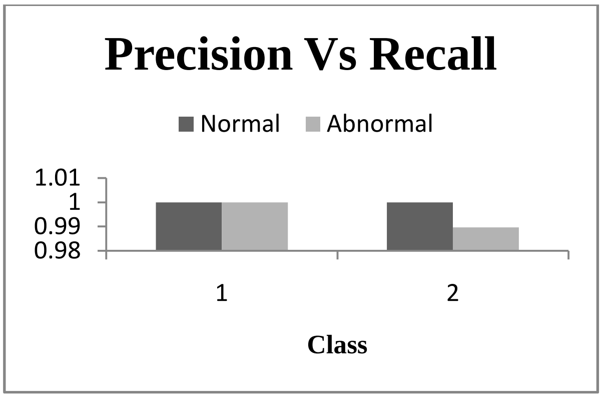

Fig.15 Precision v/s. Recall curve

The performance of the proposed system has been obtained in terms of precision, recall, sensitivity and specificity. Here, precision measures the capability of the proposed system to adapt for accuracy and exactness, while recall depicts the ability of the system to obtain all the models that are relevant to the input data. Mathematically, it is given as:

$$\text{Precision} = \frac{\text{Number of True Positive}}{\text{Total Number of True positive} + \text{false positive}}$$

$$\text{Recall} = \frac{\text{Number of True Positive}}{\text{Total Number of True Positive} + \text{false negative}}$$

Eq. (14)

Fig.15 represents the precision and recall analysis, where the proposed system has illustrated average 97.11 % precision and 97% recall efficiency. Fig.16 depicts that the proposed system exhibits approximate 99.9% of sensitivity and 99.7% of specificity.

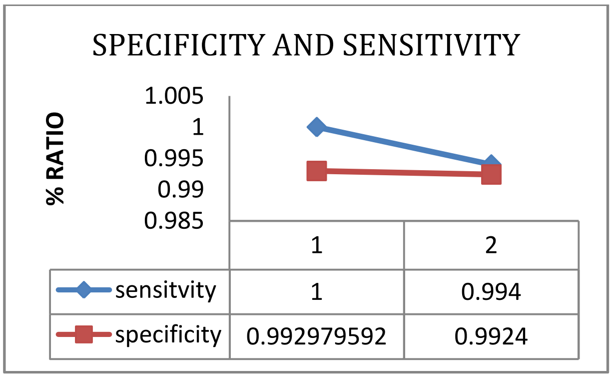

Fig.16 Sensitivity and specificity of proposed system

Fig. 16 graphically represents the specificity and sensitivity of the proposed system. It can be seen that the proposed system is more specific and sensitive i.e. for normal class sensitivity of the proposed system is 100 and for normal class 99.4. The same way specificity of proposed system for class 1 is 99.29 and for class 2 99.24.

Table 5. Confusion Matrix

Class	Predicted (positive)	Predicted (Negative)
Class 1	2	3
Class 2	1	7

VI. CONCLUSION

In this paper, a powerful signal processing technique taking into account wavelet for extraction of respiratory movement from PPG signals, even in circumstances of PPG signal getting defiled by serious MA has been proposed and actualized. A model was produced for concurrent recordings of PPG and respiratory signals. Results displayed higher level of connection of the extricated respiratory signal with the initially recorded signal and great morphological likeness notwithstanding when the PPG are adulterated with serious MAs. Higher estimations of figured similitude parameters and in addition lower estimations of mean, standard deviation as a measure of signal deviation obviously demonstrated that the PPG-determined respiratory signal can be utilized for checking patients' breathing action. The heartiness of the proposed strategy is to expel movement antiquities from the signal. Further, the heartiness can be completely examined if PC reproduced MAs are accessible as databases. From a clinical perspective, 'respiratory action' incorporates such descriptors as respiratory rate and profundity, and in addition quantifiable data about the level of gas trade really occurring. Results show proposed framework's execution well and give better exactness, accuracy and review.

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BIOGRAPHIES

B.M. Jayadevappa received the ME degree in Electronicsand Control from Birla Institute of Technology and Science, Pilani, Rajasthan, India, in 1994. He has 29 years of teaching and 6 years of research experience. His research interests are biomedical signal processing and rehabilitation engineering. Currently, he is Professor and Head, Department of Electronics and Instrumentation Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India.

Mallikarjun S. Holi received the PhD degree in Biomedical Engineering fromIndian Institute of Technology, Madras, Chennai, India, in the year 2004. Hehas 22 years of teaching and 14 years of research experience. His researchinterests are biomechanics, biomedical signal and image processing, andrehabilitation engineering. He was awarded Institute Merit Prize for the BestAcademic record in M.Tech. (Biomedical Engineering) program for 1995–1996from Indian Institute of Technology, Madras. He is recipient of TravelAward from IEEE-EMBS in 2001 and from IBMS & JSBMR in 2003.Currently, he is Professor and Chairman, Department of Electronics andInstrumentation Engineering, University B.D.T. College of Engineering,Davangere, Visvesvaraya Technological University, Karnataka, India.