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A MODIFIED FRAMEWORK TO ESTIMATE BREATHING RATE FROM ELECTROCARDIOGRAM, PHOTOPLETHYSMOGRAM, AND BLOOD PRESSURE SIGNALS BY USING ROBUST KALMAN FILTER

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Abstract : A crucial physiological characteristic that is frequently assessed in a variety of therapeutic contexts is breathing rate (BR). It is still frequently measured manually, though. In this study, a novel methodology is put forth for estimating the BR from a blood pressure (BP), photoplethysmogram (PPG), or electrocardiogram (ECG) signal. The framework takes advantage of both time and frequency domain data to extract respiratory signals using Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) techniques. With the use of a Robust Kalman Filter (RKF) that incorporates a Signal Quality Index (SQI), our technique was able to operate adequately even during periods when the signals were noticeably distorted. The output signals are integrated via state vector fusion, and then the BR is calculated. The MIT-BIH Polysomnographic and BIDMC datasets were used to evaluate the framework on two publicly accessible clinical databases. The mean absolute percentage error (MAPE) was used to evaluate performance. The outcomes showed great accuracy, with MAPEs on the two databases for ECG signals of 4% and 4%, 7% for PPG signals, and 5.4% for BP signals. The outcomes also showed a remarkable robustness to noise at 0 dB. Consequently, this system might be useful for BR monitoring in environments with excessive noise.

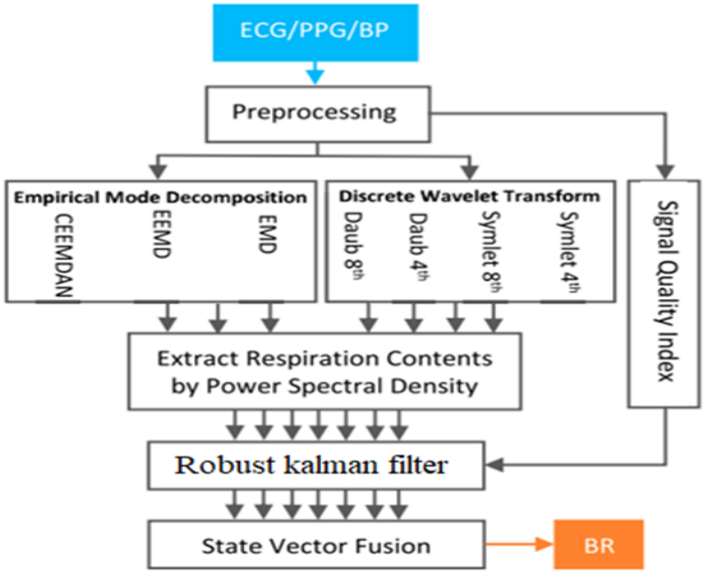
IndexTerms - Electrocardiogram (ECG), photoplethysmogram (PPG) and blood pressure (BP) signals. Empirical mode decomposition (EMD)and discrete wavelet transform (DWT).

I. INTRODUCTION

Breathing Rate (BR) is a crucial physiological metric that may be assessed from patients in a variety of situations, such as ERs, ICUs, and hospital wards. The sensitive indicator of patient deterioration known as BR has been demonstrated. Elevated BRs, for instance, may occur before cardiac arrest or respiratory failure.

Additionally, BR can be utilised as a predictor of in-hospital mortality. Additionally, BR is used to diagnose a number of illnesses, including sepsis and pneumonia. Direct breathing monitoring sensors based on methods like spirometry, pneumography, or plethysmography are readily available. The use of these sensors is restricted to particular clinical situations, such as stress testing and sleep apnea diagnosis, because they might affect breathing patterns and be intrusive. Less intrusive respiratory monitoring techniques might be more well-tolerated by patients and hence used in a wider variety of clinical situations.

The Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) can be used to decompose a signal into a set of signals, allowing one to extract a respiratory signal (herein referred to as ECG-Derived Respiration (EDR), PPG-Derived Respiration (PDR), or BP-Derived Respiration (BDR) signals. They have been widely applied to ECG signals.Since EMD and DWT methods are not absolutely superior to each other, we have used both of them simultaneously to improve the performance of the estimator. Having obtained a respiratory signal, Power Spectral Density (PSD), a measure of a signal's power across the range of frequency content, has been widely used to estimate BR. The Welch periodogram is a technique for estimating the PSD which averages power spectra calculated from shorter segments of the input signal to provide increased robustness to noise.



FIGURE(1):PROPOSED BLOCK DIAGRAM

II. MATERIALS AND METHODS

Pre processing stage and Extracting respiratory signals and empirical mode decomposition (EMD) and Discrete wavelet transform (DWT). Basically First pre processing stage has ECG and PPG BP signals has contain some hign frequency noise and it having DC component. Second stage has decompose this signals into components by using EMD and DWT. Power Spectral density of the components are used to corresponding respiratory signals (EDR,PDR,BDR).thirdly the SPI is calculated over time for each respiratory signals and use the robust Kalman filter (RKF) remove noise from each respiratory signal and signal quality index in the RKF is more evident in the noisy parts which have low quality. Fourthly state vector fusion is used to derive a single respiratory signal and finally the breathing rate (BR).

PRE PROCESSING STAGE

When the sensors or transducers are generating ECG and PPG and BP signal has contain some high frequency noise and DC components are removing this stage by using 3rd order Butterworth high pass filter. Now take BR assumption 5 breaths per minute corresponding (0.083HZ) for window length 11 and high frequency noise removed for using moving average filter.

EXTRACTING RESPIRATORY SIGNALS

Extracting respiratory signals from physiological data or sensor readings is a crucial step in various medical and healthcare applications. Accurate extraction of respiratory signals is essential for monitoring a patient's respiratory rate and detecting anomalies. EMD and its extended algorithm and DWT method use extracting a set of respiratory signals from input signals.

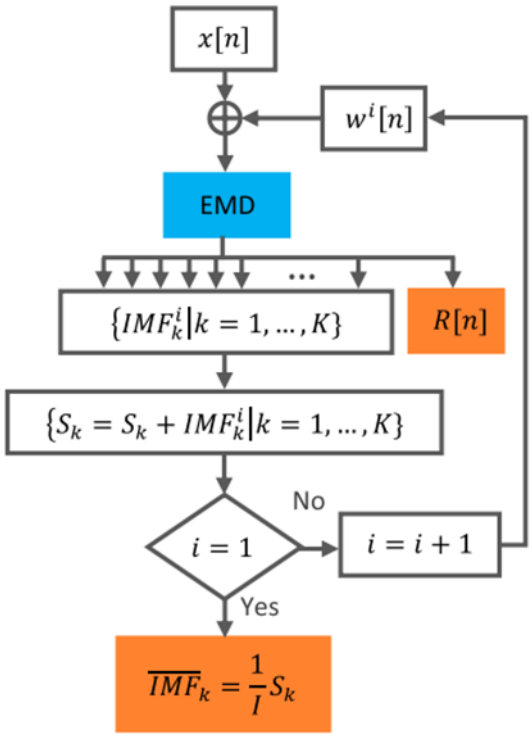
A. EMPERICAL MODE DECOMPOSITION (EMD)

EMD is an adaptive fully data-driven method for analyzing non-linear and non-stationary signals. By exploiting both local temporal and structural characteristics, time series are decomposed into individual components by expressing the original signal as a linear combination of zero-mean amplitude and frequency modulated functions called Intrinsic Mode Functions (IMFs), and a residual

(1) The number of zero-crossings and positive/negative peaks should either be equal or at most differ by one; and

(2) The mean of upper and lower envelopes must be zero. The mode mixing problem arises when the signal contains intermittent processes

Mode mixing is defined as a single IMF containing signals of widely disparate scales or a signal of a similar scale residing in different components. This phenomenon makes the physiological meaning of individual IMFs unclear. To alleviate this problem a Noise-Assisted Data Analysis (NADA) method is proposed.



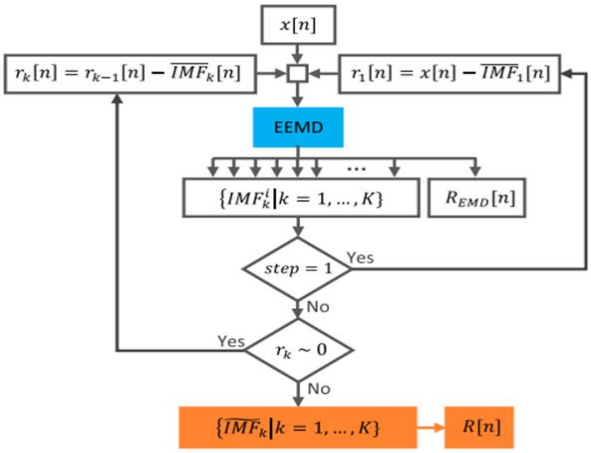
FIGURE(2):EMD BASED DIAGRAM

B. COMPLETE ENSEMBLE EMPERICAL MODE DECOMPOSITION ADAPTIVE NOISE(CEEMD)

The advantages of CEEMDAN over EEMD are that it achieves a negligible reconstruction error and solves the problem of different number of modes for different realizations of signal plus noise. EEMD and CEEMDAN methods. The steps of the EEMD and CEEMDAN methods, are shown in the two flowcharts in Figs.2 and 3, respectively.

To determine which IMFs contain respiratory content, the PSD of each IMF is calculated, and the dominant frequency band of each IMF is identified as the 6dB bandwidth around the highest amplitude of the PSD. Afterwards, the IMF with the closest frequency band to the respiratory frequency band (6 to 33 bpm [0.10Hz, 0.55Hz]) is chosen as the EDR, PDR, or BDR signal. EDR and PDR signals extracted from a 60-second window of ECG and PPG signals respectively (from BIDMC01).

These were extracted using EMD, EEMD and CEEMDAN methods. The dashed red and green lines indicate the dominant frequency ranges of the reference respiratory signal and EDR/PDR signals, respectively. The dominant frequency bands of both extracted EDR and PDR signals by CEEMDAN method are the closest to the dominant frequency band of the reference respiratory signal.



FIGURE(2):CEEMDAN BASED DIAGRAM

III. DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform

The Wavelet Transform (WT) is a time-frequency signal analysis methods that offers simultaneous interpretation of the signal in both time and frequency domains, allowing local transient or intermittent components to be elucidated. The WT and inverse transform can be computed discretely, quickly and without loss of signal information by considering the multi-resolution algorithm.

In this study, respiratory components of ECG, PPG, or BP signals were extracted using the DWT with four different mother wavelet functions: Daubechies of 4th and 8th order and Symlet of 4th and 8th order. After applying the DWT with these wavelet functions, the PSDs of each detail signal were calculated. To identify the detail signal containing respiratory content, the dominant frequency bands of the obtained PSDs were compared to the frequency band of respiration ([0.10Hz, 0.55Hz]).

1.SIGNAL QUALITY INDEX

Hjorth parameters were originally proposed to extract features from the spectrum of the Electroencephalographic (EEG) signal by calculating

$$\overline{w}_n = \int_{-\pi}^{\pi} w^n P(e^{j\omega}) d\omega \qquad (1)$$

Where P ($e^{j\omega}$) is the power spectrum of the signal as a function of angular frequency. ω = 2πf, with f in cycles/second. By averaging in the time domain, the spectral moments of a signal can be estimated using a shifting overlapping window as follows using a shifting overlapping is

$$\tilde{\overline{w}}_i \approx \frac{2\pi}{L} \sum_{k=n-(L-1)}^{n} \left(x^{(\frac{i}{2})}(k)\right)^2 , \qquad (2)$$

Where $x^{(i/2)}$ (k) is the i/2 derivative of x(k) and L is the window duration (L = 4s here). The SPI uses the Hjorth descriptors to calculate an index for assessing the quality of signals. Here we have used SPI as an SQI to assess the quality of signals as follows

$$\Gamma_{SPI}(n) = \frac{\overline{w}_2(n)^2}{\overline{w}_0(n)\overline{w}_4(n)} \quad . \qquad (3)$$

Where Γ_{SPI} varies between 0 (corresponding to complete noise) and 1 (corresponding to a pure sinusoid), indicating low and high signal quality respectively. For instance, the variation for the PPG signal of BIDMC01, which approaches 0 during low quality periods and 1 during high quality periods.

IV. ROBUST KALMAN FILTER

There are seven respiratory signals in the proposed algorithm at this point, each with a corresponding SQI parameter. Applying a KF or RKF to the respiratory signals at this stage improves their quality. Both a KF and an RKF have the ability to remove noise from a signal and then reconstruct it using a dynamic model. However, a KF can only accept a linear model, whereas an RKF can accept a nonlinear dynamic model.

Since a model's accuracy can be decreased during the linearization process for use with a KF, an RKF may perform better than a KF. In this study, the RKF is optimized using the SQI parameter. Details are now provided on the use of the KF and RKF. The KF is a well-known optimal state estimation method that has been proven to be the optimal filter in the Minimum Mean Square Error (MMSE) sense. The application of the KF and RKF is now described in detail. The KF is a well-known technique for estimating optimal states, and it has been shown to be the best filter in terms of Minimum Mean Square Error (MMSE).

$$R_n \rightarrow R_n e^{(SQI_n{}^{-2}-1)} \qquad (4)$$

Since most systems in practise are nonlinear, the estimation accuracy must first be reduced when using the KF to approximate nonlinear dynamical models in linear form. The RKF is an extension of the standard KF that takes into account nonlinear dynamic estimate of a stochastic signal's states. McSharry et al.'s dynamic equations are employed as the state model in this paper. Three coupled ordinary differential equations make up the dynamic model.

Using the initial nonlinear dynamical model of the signal, the RKF estimates the state vector throughout the time propagation step. The RKF uses an interaction between a dynamical model and data, which is produced by the Kalman Gain (KG), to estimate the state vector in each iteration. The measurement noise covariance (R) value and KG have an inverse relationship. As a result, measurements of inferior quality, which have greater R values, have lower KG values. For each cycle, lowering the value of

KG lessens the impact of measurements on estimation, and vice versa. The following is a representation of a multiplicative modification of R.

where SQI n is the SQI of the n th sample of data which is replaced by SPI in this paper, as follows.

$$SQI_n = \Gamma_{SPI}[n] \qquad (5)$$

A)STATE VECTOR FUSION

At this stage of the proposed algorithm, there are 7 respiratory signals. State vector fusion is then used to fuse the 7 signals to provide a single respiratory signal. By considering the state error covariance matrices that are achieved from RKF, local estimate signals are combined in a MMSE sense, as follows.

$$\hat{x}_n = (\sum_{j=1}^{J} (P_n^j)^{-1})^{-1} \sum_{j=1}^{J} [(P_n^j)^{-1} \hat{x}_n^j] \qquad (6)$$

where $\hat{x}_n$ is the global estimate of state at each time n. J represents the number of signals that must be fused, which in our case is equal to 7 (J = 7). The $(P^j_n)^{-1}$ and $\hat{x}^j_n$, respectively are the inverses of the state error covariance matrices and the local state vector estimate for each of the 7 respiratory signals. According to this, respiratory signals with better performance contribute more to obtaining the state vector. In accordance to estimating breathing rates, for each sample of the 7 respiratory signals a global estimate of state is obtained as a single fused signal.

B)ESTIMATING BREATHING RATES

At this stage used to detect the peaks in the fused respiratory signal. The BR was then estimated by counting the number of peaks within a time period, and expressed as beats per minute (bpm).

V. DATA BASES

At this stage used A renowned hospital and research facility connected to Harvard Medical School is known as MIT BIDMC (Beth Israel Deaconess Medical Center). They have several databases and research tools, but you don't mention which particular database in your question. In addition to managing a large number of databases pertaining to healthcare, clinical trials, patient records, and other topics, MIT BIDMC is actively involved in numerous medical and scientific research projects.

I don't specifically know if there is a BIDMC (Beth Israel Deaconess Medical Center) database that is open to the general public as of my most recent knowledge update in September 2021. Being a renowned teaching hospital and a member of Harvard Medical School, BIDMC may have access to a number of private databases and research tools.

I advise visiting BIDMC's official website or getting in touch with them directly through their official channels if you're searching for specific data or information pertaining to the organization. Researchers, healthcare professionals, or certain collaborators may have access to their research databases, clinical data repositories, or other resources, but access and availability may be restricted by their policies and procedures.

VI. ADITION OF NOISE

You appear to be talking about a test of the reliability of a method for calculating blood pressure (BR) from electrocardiogram (ECG), photoplethysmogram (PPG), and blood pressure (BP) signals by including various amounts of white noise. To assess how well the framework performed in various noise environments, the signal-to-noise ratio (SNR) was modified, with SNR values stated as SNRdB = 0, 5, 10, 20, 40.

$$SNR_{dB} = 10 \log_{10} \frac{\sum_{n=1}^{N} x[n]^2}{\sum_{n=1}^{N} (y[n] - x[n])^2} \qquad (7)$$

where N is the total number of samples, y is the denoised signal, and x is the original signal.

A)STASTICAL ANALYSIS

Three metrics were used to assess the effectiveness of a set of algorithms for BR (Beat-to-Beat Heart Rate) estimate, one of which is the Coverage Probability (CP) with a specified bound of 2 bpm (beats per minute). Here is a description of the measure and its methodology.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\mu}_{BR}(i) - \mu_{ref}(i)|, (bpm) \qquad (8)$$

B)MEAN ABSOLUTE ERROR

Mean Absolute Error (MAE) is a metric that assesses a predictive model's precision and is frequently employed in the context of regression analysis. It measures the typical absolute difference between a dataset's actual values and the values that were anticipated. In other words, it assesses the average deviation between the model's predictions and actual results.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\mu}_{BR}(i) - \mu_{ref}(i)|, (bpm)$$

Where $\hat{\mu}_{BR}$ is the actual breath rate and μ_{ref} is the reference breath rate in BPM.

To put it another way, you figure out the absolute difference between each predicted value and its corresponding actual value, add up all of these absolute differences, and then divide by the entire number of data points (n) to get the average.

Due to its direct measurement of the average size of model errors, MAE is an easy-to-understand metric. Lower values denote greater performance and give a measure of how well the model's predictions match the actual data. When dealing with datasets that contain outliers or when you want to stress the significance of mistakes of a consistent size, MAE is an excellent option because it is less sensitive to outliers than certain other error metrics like Mean Squared Error (MSE).

C)MEAN ABSOLUTE PERCENTAGE ERROR

In statistics and data analysis, the Mean Absolute Percentage Error (MAPE) is a regularly used metric to assess the precision of a forecasting or prediction model. The average absolute percentage difference between a dataset's actual values and expected values is quantified by MAPE. It is very helpful for evaluating a model's performance in terms of percentage inaccuracy.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{\hat{\mu}_{BR}(i) - \mu_{ref}(i)}{\mu_{ref}(i)}\right| \times 100, (\%)$$

To put it simply, you find the percentage difference between each predicted value and its corresponding actual value, calculate its absolute value, add up all of these absolute percentage differences, and then find the average by dividing by the total number of data points (N).

MAPE is helpful when you wish to evaluate a model's correctness in a method that is independent of scale, making it appropriate for contrasting models across various datasets or domains. Since the prediction error is expressed as a % of the actual value, it is simpler to understand in many situations. It does have some limits, particularly when working with small actual values close to zero, which might result in errors that are either undefinable or have excessively large percentages. Other error metrics, like MAE or RMSE, may be more suited in such circumstances.

VII. OUTPUTS AND RESULTS.

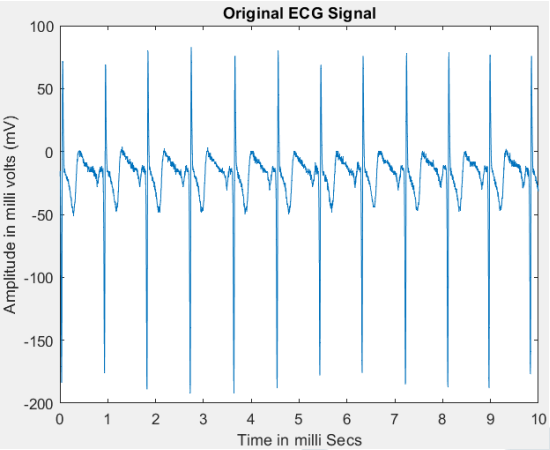


FIG4: original ECG signal

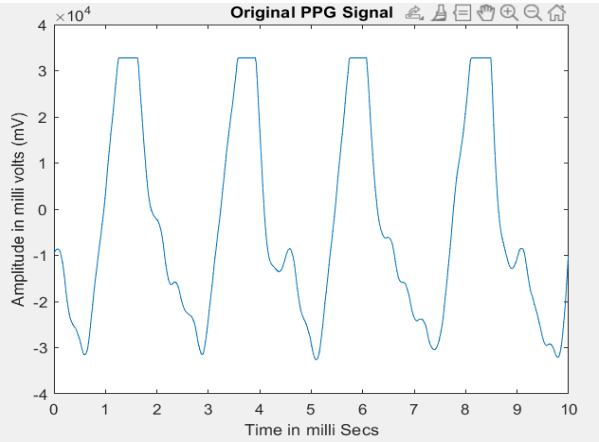


FIG5: original PPG signal

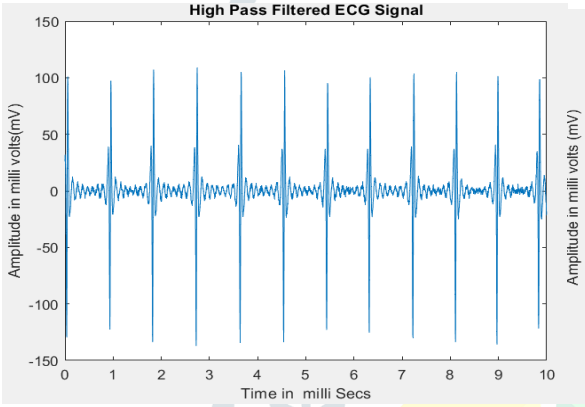


FIG6: HIGH PASS FILTER ECG signal

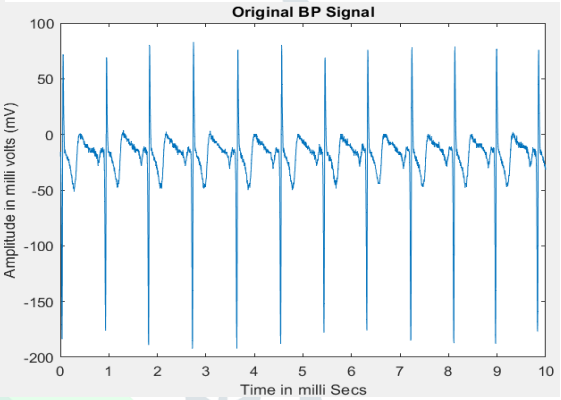


FIG7: original BP signal

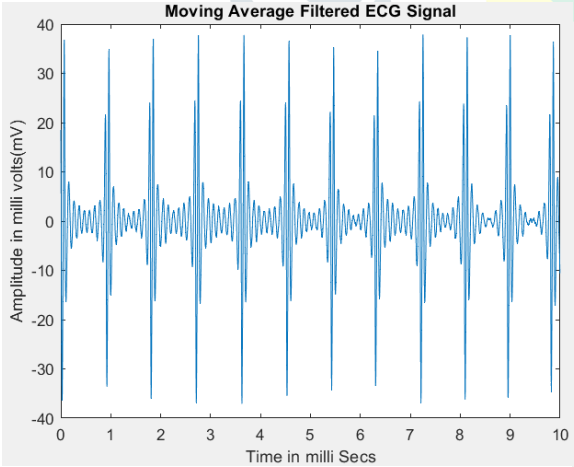


FIG8: moving average filter ECG signal

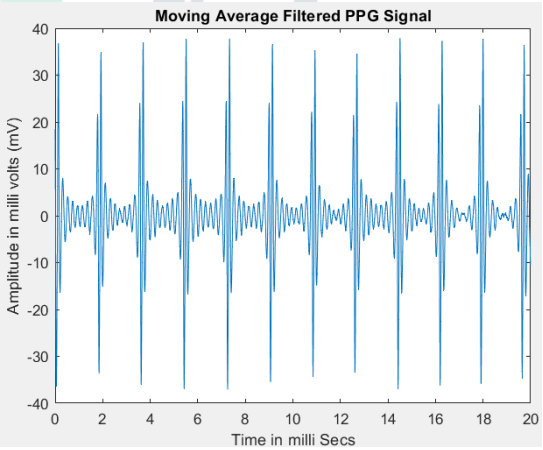


FIG9:moving average filter PPG signal

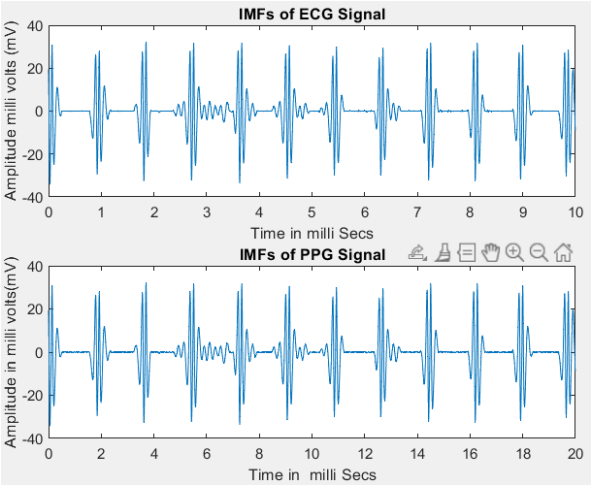


FIG10: imf ECG signal

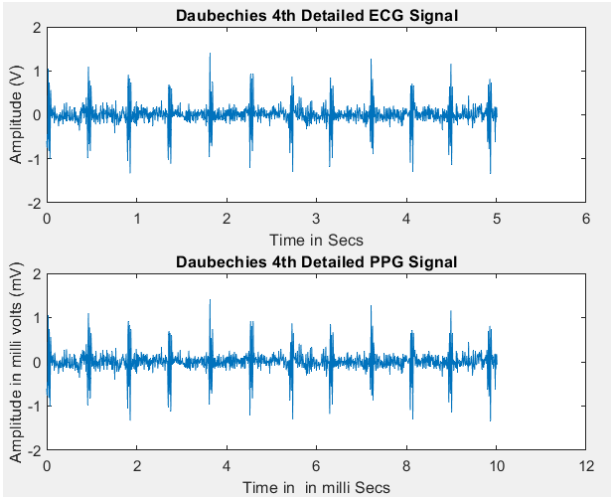


FIG11: DAUBECHIES 4TH ECG PPG signal

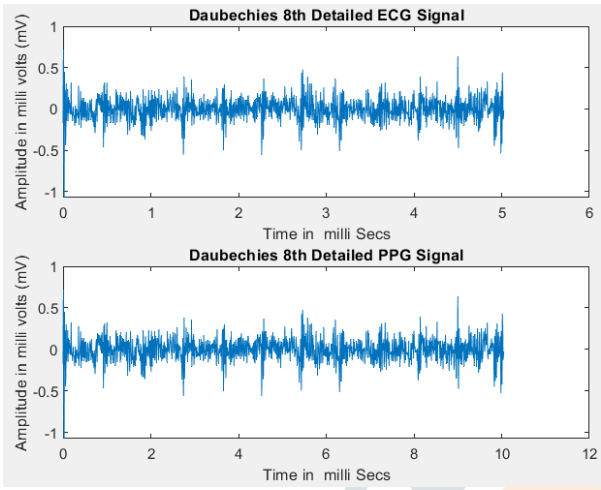


FIG12:DAUBECHIES 8TH ECG PPG signal

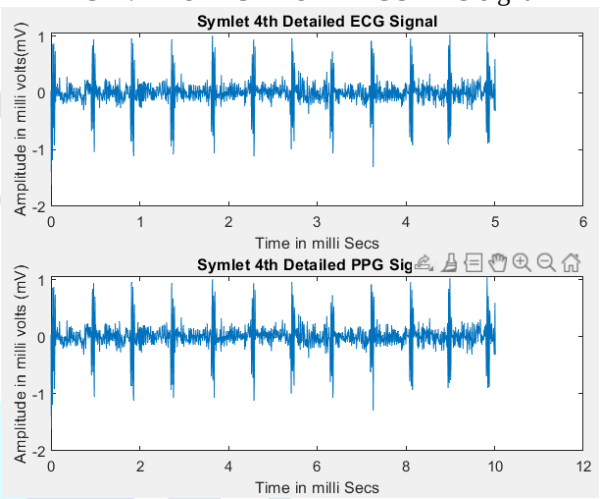


FIG13: Symlet 4th ECG PPG signal

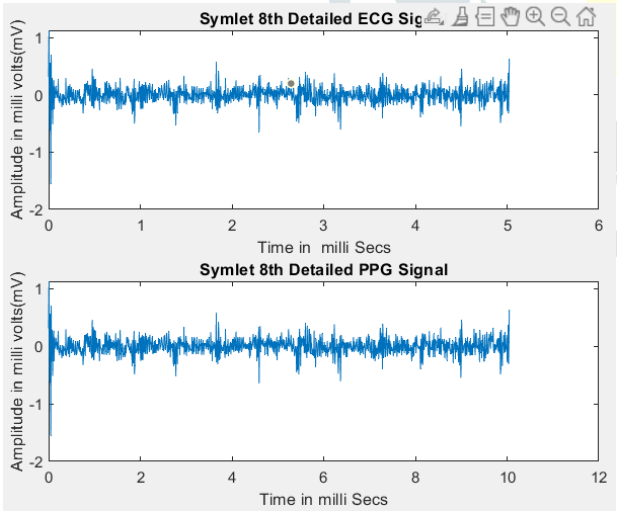


FIG14: Symlet 8th ECG PPG signal

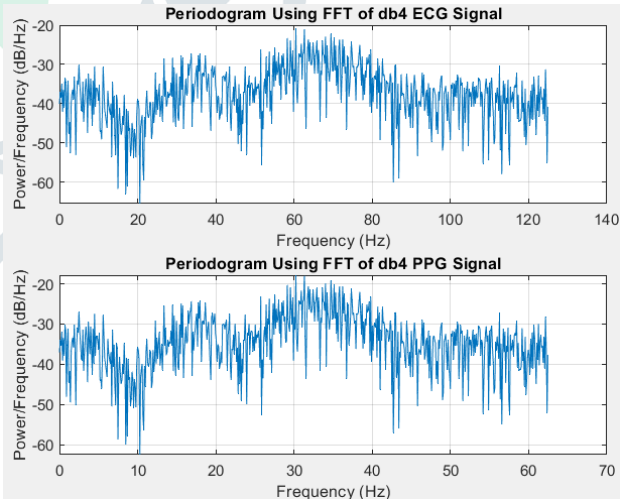


FIG15: periodgram FFT db4 ECG PPG signal

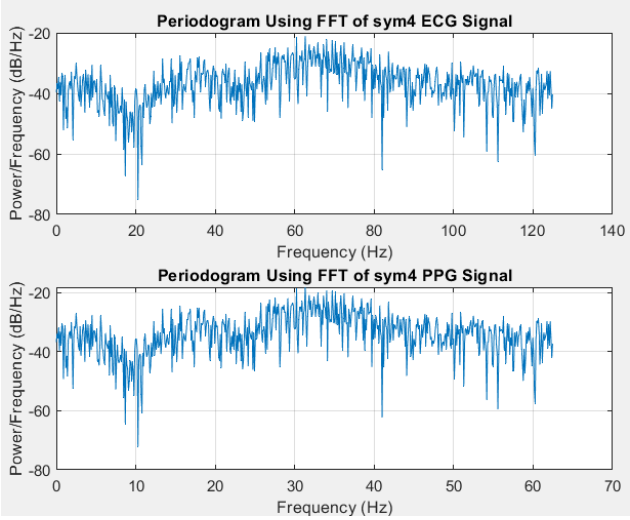


FIG16: periodogram FFT sym4 ECG signal

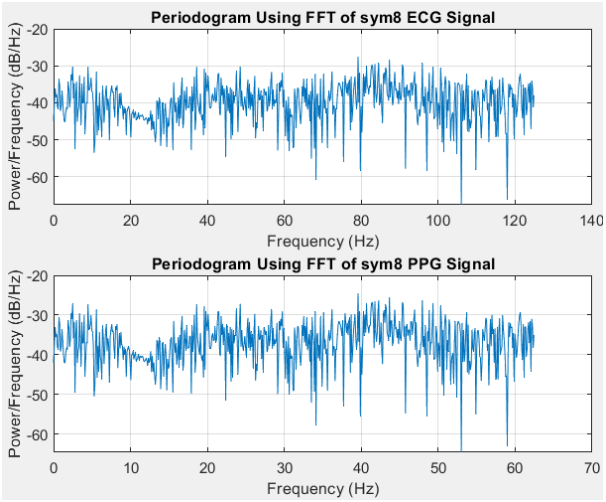


FIG17: periodogram FFT sym 8th ECG PPG signals

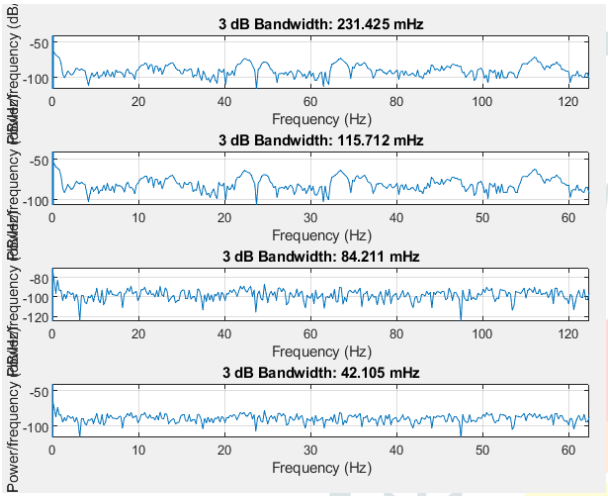


FIG18: 3dB ECG PPG signal

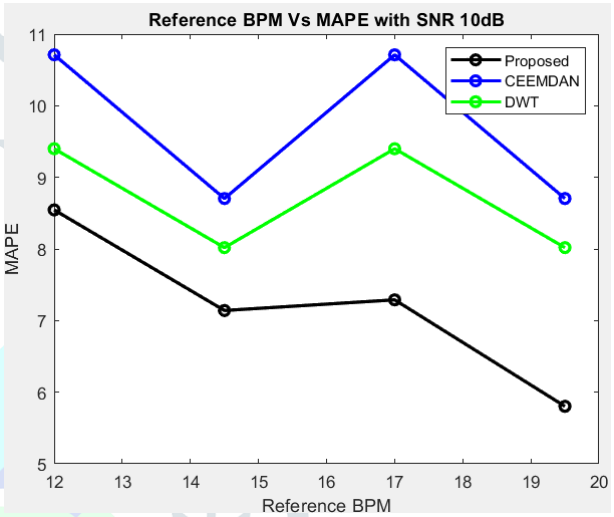


FIG19:REFERENCE BPM VS MAPPE 10dB

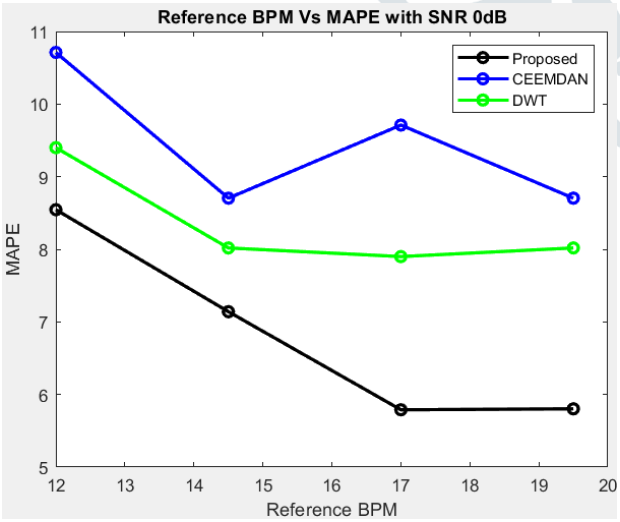


FIG20:REFERENCE BPM VS MAPPE OdB

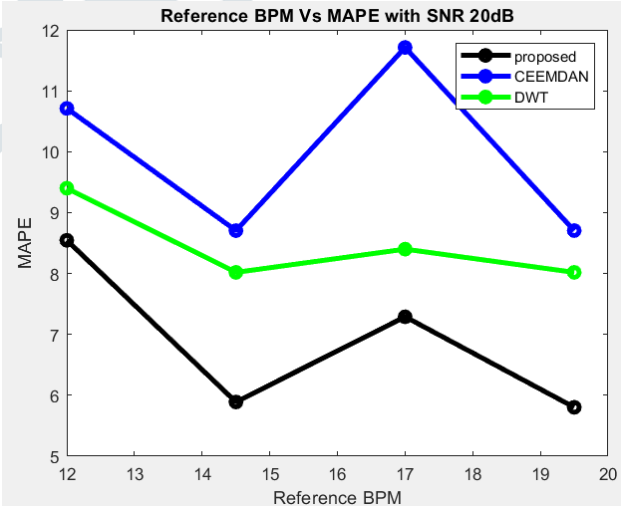


FIG21: REFERENCE BPM VS MAPPE 20dB

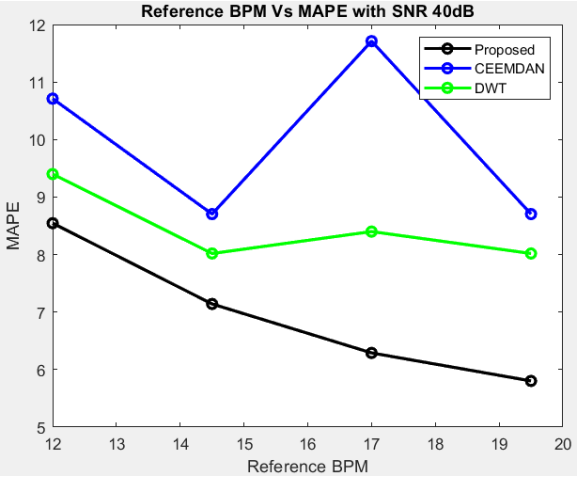


FIG20:REFERENCE BPM VS MAPPE 40dB

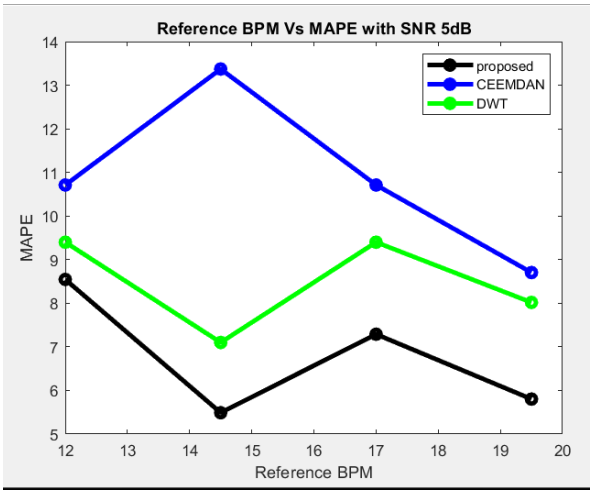


FIG21: REFERENCE BPM VS MAPE 5dB

CONCLUSION;- In this paper, we employ a basic neural network for the detection of abnormal heart rhythms in ECG recordings. Our network is made to take two types of input: a feature vector made up of PCA coefficients and a temporal feature vector made up of five consecutive beats and the ventricular R-R interval rate.We have used the moving average filter in this instance to further reduce the noise present in the input signal. While maintaining superior anomalous signal identification accuracy and acceptable accuracy in challenging records, the suggested method can achieve minimal complexity in typical clinical recordings. By substituting several activation functions with approximations and mapping to fixed point after retraining, the approach was transformed to an embedded platform with the least amount of implementation loss and the least amount of implementation expense. A computationally challenging design in comparison to the state of the art.

We exhibited a considerable reduction in the total system power consumption when the wireless transmission is gated using a binary classifier so that only irregular beats are broadcast as opposed to continuous data transfer.

REFERENCES;-

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