IJCSN International Journal of Computer Science and Network, Volume 4, Issue 5, October 2015
ISSN (Online) : 2277-5420 www.IJCSN.org
Impact Factor: 0.417

Embedded Hardware for Online Monitoring of ECG Signal

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Abstract - The proposed work presents the principle of low cost embedded system which gives essential ECG monitoring system. For ECG signal in real time, embedded C is used for programming the proposed system hardware. Embedded system consists of 32bit ARM LPC2138, MAX232, Amplifier circuit block, ECG electrodes. System gives essential real time ECG signal values. ECG signal related parameters are analyzed like wave's amplitude, heart beats, blood pressure and RR interval. It also gives normal and abnormal status of ECG signal. Different algorithms like wavelet transform, extended kalman filter, extended kalman smoother and linear discriminant analysis classifier are used for filtering and analysis of the ECG signal and its parameters respectively. Wavelet Transform gives better Accuracy of 97.20% and Detection error ratio of 0.064, Positive Prediction of 93.91% as compared with EKF and EKS. System have advantages like low cost, better results in real time, versatility.

Keywords - *Embedded ECG Monitoring System, Detects Normal and Abnormal Status, Wavelet Transform, Extended Kalman Filter, Extended Kalman Smoother and LDA.*

1. Introduction

Electrocardiogram (ECG) saves the temporal profiles obtained through electrical excitation processes in the myocardium in the order of waves, peaks, and lines. ECG gives the image of the electrical production and reflects the excitation processes in the heart by the electrodes joined to the surface of the body. The ECG of the patients with cardiovascular disease is controlled over days and weeks for major function recognition and emergency help. The system arranges the ECG signal in various types of five waves reflecting the various functions of the heart during the period of cardiac cycle. These waves are known as P, Q, R, S and T. Three important deflections or waves are: the P wave, the QRS complex, and a T wave. There are two time intervals of clinical importance which includes the PR interval and QRS duration. Our main aim is to get better ECG signal and detect QRS complex and its duration in real time and their respected parameters. The Hospital industry gets advantage from this system and gives more reliable equipment, saving more lives and generating worth data for research and diagnosis. It is interesting to make a system for people suffering from heart diseases. The system we have proposed & implemented is a simple prototype of an embedded system for such scenario.

This paper presents a work in which embedded system incorporates the microcontroller ARM7LPC2138, Diagnostic Electrode, Amplifier circuit block, LCD display, MAX232. Components are connected around the microcontroller for the proper detection of ECG real time. Then the signal will be displayed on ECG monitoring system which gets analyzed. ECG signal related parameters like P, Q, R, S, T waves amplitude, Heartbeat, Blood pressure etc. are analyzed on Visual Basic. The amplitude values are stored and visualized. The analysis of ECG signal sensitivity, accuracy, positive prediction, Error detection is done in MATLAB. Parameter analysis is done through algorithm and ECG signal is plotted on ECG monitoring system.

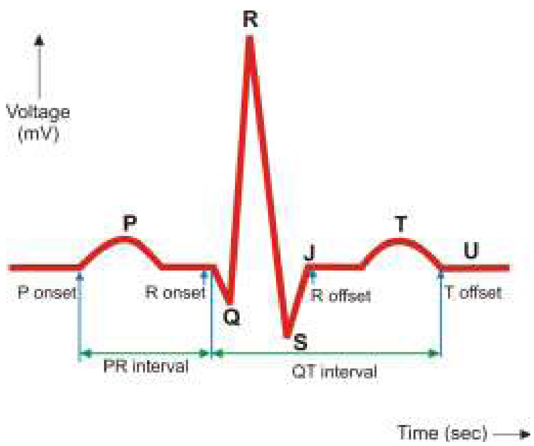

Fig. 1 ECG waveform with the standard ECG intervals

Table 1: Standard ECG waves and intervals

Sr. No	***Waves and Intervals***	**Amplitude and Time**
1	P wave	0.25mV
2	R wave	1.6 mV
3	Q wave	25 percent of R wave
4	T wave	0.1 to 0.5 mV
5	P-R Interval	0.12 to 0.20 sec
6	Q-T Interval	0.35 to 0.44 sec
7	S-T Interval	0.05 to0.15 sec
8	P wave Interval	0.11 sec
9	QRS Interval	0.09 sec

The paper is organized as follows: Section II gives brief overview about the previous work., Section III gives information about system architecture and explanation of respective Blocks, Section IV gives design flow of ECG monitoring system, Section V gives information about different methods used for filtering and analysis and Section VI gives the conclusion.

2. Previous Work

Many researchers have investigated various methods for proper peak detection of QRS complex. Till now, the various methods are developed for proper QRS detection. Hilbert transform and squaring function based algorithms are used for invention in threshold detection [4]. Hilbert Transform and Wavelet transform methods are used for Suppression of the unwanted P/T wave noise by Fie Zang [5]. Pan-Tompkins detection algorithm is used for Real time QRS detection to correct the baseline and to make it horizontal [6]. Dual-slope QRS Detection Algorithm is used to calculate the slope of both the sides of peak in ECG signal [7]. The Control based QRS detection algorithm is used for various cardiovascular diseases to test the Performance Evaluation of Proposed Algorithm [8-9]. The algorithm used for R peak from the level crossing sampled data gives compressed volume of data [10 -11]. But the algorithms that were proposed in previous QRS detection method were only detecting QRS depending upon the database of the patient given as an input. Our system analyses database parameters features in real time along with the hardware for better understanding.

3. Proposed Work

3.1 Hardware Development

The figure shows the biomedical application of the embedded system to detect the heart beats, normal and abnormal ECG signal that monitors the patient influenced by arrthymias with risk for heart attack [19]. It gives a correct evaluation reading of the heart performances.

The detailed description of each block is given below:

1. Microcontroller ARM 7

ARM microcontroller (ARM7LPC2148) is the heart of the Embedded System which collects and stores various parameters from different test results and gives action on results obtained in monitoring. Controller sense signals from input in real time. It processes and transmits signal

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to the output to display on Monitoring System. The signal obtained from input electrode will be converted into digital form using analog to digital converter. The Liquid-Crystal Display (LCD) block is provided for visual display of the message with desired values and continuously displays the measured parameters. It controls actions based on the software programs stored in the memory. Every time, all the results of the tests are compared with the standard parameters such that we can decide whether the person is suffering from any abnormalities or not depending upon ECG obtained. Similarly the monitoring patient's ECG test will also help to compare and all the test results are compiled and the report is sent to the medical practitioner through the Message.

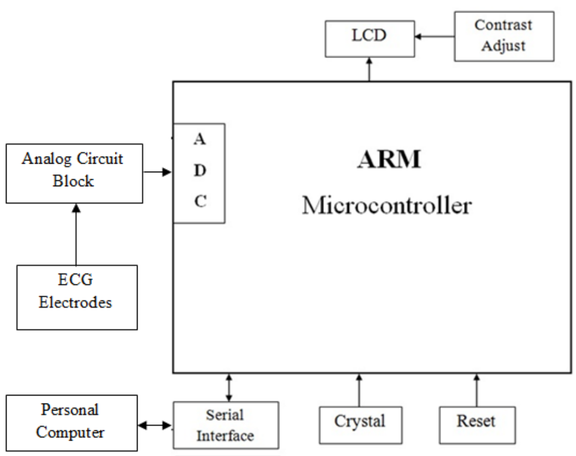

Fig. 2 Block diagram of proposed system

2. LCD Display

The LCD display is an output device which is interfaced on the board with the microcontroller. Instant data report of either freshly obtained or the compared and the final results are displayed. It also shows the complete test and their related results and final results after analyzing whether the person with ECG signal is properly detected or not.

3. Suction Electrodes

Body surface recording electrode called as suction electrode. Metallic suction electrode is often used as a precordial electrode on clinical electrocardiograph. There is no need for strap or adhesive and can be used frequently. It has higher source impedance since the contact area is small. Electrodes are connected to RIGHT Arm, LEFT Arm and RIGHT leg that detects electrical activity of heart or also called as pulse.

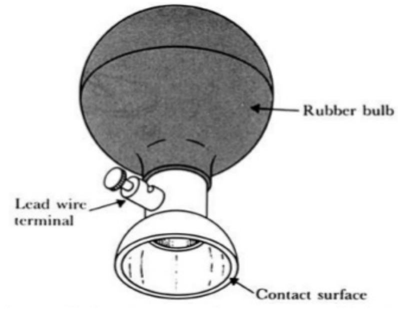

Fig.3 Electrode connect to body surface

4. Amplifiers Circuit Block

Amplifier circuit block consists of Monolithic instrumentation amplifier (AD620), Optocoupler (MCT2E) and Ultra low offset voltage operational amplifier (OP07). Electrodes are connected to the input of AD620 to detect heart electrical activity of patient in real time. It requires low power, low supply voltage and introduces low noise in signal. It detects correct heart pulse which can be maximum or minimum depending upon the patient but if it reaches beyond maximum limit, it can damage further circuit. Due to these reasons, Optocoupler(MCT2E) is used here. MCT2E circuit is introduced to protect from damage. It sets the input pulse which requires to further circuit for processing. After that, OP07 circuit is included here to reduce the noise in signal. It acts as the precision filter. After each circuit performance, we get noise free signal called as analog signal which is provided to the controller for further processing.

5. Max232

The microcontroller has built-in RS232 interface that permits serial communication with a computer via serial port. A classic MAX232 achieves the RS232/ TTL conversion (physical layer protocol). With this point to point link, we can transmit the ECG signal to the Personal Computer(PC) to store voltage values on hard disk and treatment in real-time.

3.2 Software Development

This subsection gives the idea for designing ECG monitoring system. The required design flow of monitoring system is shown in figure below.

System starts its work, selects port for communication with embedded system and then it initializes the electrodes. After that, whichever input comes from the electrodes, it gets extracted using amplifier circuit block if

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electrodes are placed properly. Then it sends the obtained values to the controller in digital form after analog to digital conversion.

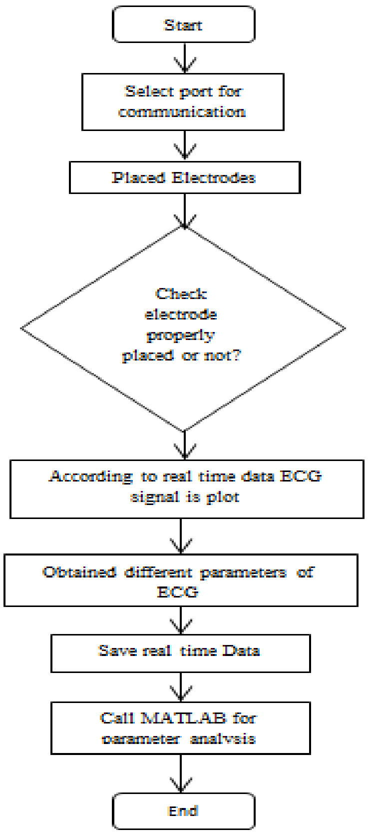

Fig. 4 Design Flow Chart

Then those values are also displayed on LCD. After this processing, obtained data is given to PC in serial format. Then it plots ECG signal according to the data of patient obtained in real time and on the basis of that data, different types of parameters related to patient ECG is visualized on monitoring system. Then it plots the graph on VB. It saves the database of the patient in the specific drive. Those collected data analysis will be performed in MATLAB using various algorithms. After that, the parameter gets analyzed and it shows the status of the patient. Data comes from the system which is connected to the PC with the help of RS232 for the serial communication. Visual Basic tools are designed to plot the ECG signal. The port 3 is connected with the computer. After that, it checks whether the electrode is correctly placed or not. If yes, then plot the ECG signal on VB and save the values. After that, VB calls MATLAB for analyzing different parameters of ECG signal. ECG monitoring system is designed by using different buttons in Toolbox. MATLAB is used to perform analysis of different parameters of the ECG signal. Methods are used, which plays an important role in analysis of parameters.

4. Methods Used for Filtering

This section provides the ECG signal obtained in real time. It contains little noise and because of this, filtering methods are used to denoising signal as follows:

4.1 Wavelet Transform

Biomedical signals like ECG are non-stationary. Wavelet transform is found to be the efficient solution for processing a non-stationary signal [13]. To the best performance in many applications, transformation require filters which provide a number of desirable properties such as orthogonal, compact support, regular and symmetry property. Wavelet Transform contains properties as shown above, making them the best choice in signal analysis. The Multi Resolution Analysis (MRA) using wavelet transform is found to be an extremely useful method in extracting ECG features accurately [14]. The wavelet transform technique is used for taking advantage of the time-scale analysis characteristics. This is implemented in MRA and successive selection of signal proves that it is the powerful tool in obtaining minute signal details. Daubechies wavelet family is found to be the most suited choice for wavelet analysis due to the similarity of the wavelet with the ECG signal [12]. Discrete Wavelet Transform (DWT) is a powerful tool for the signal processing and analysis applications. DWT can be implemented efficiently using filter banks; it provides a way to use wavelets for signal processing applications [16-18].

Wavelet transform can decompose signal into different dimensions and operate in each dimension independently. Just like Fourier transform which separates signal into different frequency sine waves that are essential for band-pass filter [12, 14]. Wavelet analysis shows the features of ECG signal in both time and frequency filed. Wavelet transform is defined as follows [15]:

If function $\varphi(t) \in L^2(R), (L^2(R)$ (space composed of square integral function in real space) and then make displacement before making an inner product with signal that is to be analyzed *f*(*t*) in different dimensions. The mathematical equation is:

$$WT(a,\tau) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{a}} \varphi\left(\frac{t-\tau}{a}\right) dt \qquad (1)$$

Multi-resolution analysis (MRA) is a useful method using orthogonal wavelet as basis function. It has multi resolution features so that we can decompose signal in different dimensions and compare with it [6]. According to this algorithm, if the signal $f(k)$ is discrete sampling data $(f(k) = c_{o,k})$, then the orthogonal wavelet transform can be described as the following equation:

$$\begin{cases} c_{j,k} = \sum_n c_{j-1,n}\, h_{n-2k} \\ d_{j,k} = \sum_n d_{j-1,n}\, h_{n-2k} \end{cases} \quad (2)$$

(j, k = 1,2,3,………..,N-1)

In this equation, $c_{j,k}$ is the coefficient, and $d_{j,k}$ is the wavelet coefficient at resolution j using a number of N *sampling* points, g and h are low pass (LP) and high pass (HP) respectively. The wavelet reconstruction is the inverse operation of the decomposition following this equation:

$$c_{j,k} = \sum_{n \in z} c_{j+1,n} h_{k-2n} + \sum_{n \in z} g_{j+1,n} d_{k-2n} \quad (3)$$

Daubechies wavelet filter is used to denoised the ECG signal. The presented method is based on decomposing the signal into Eight levels of wavelet transform by using Daubechies wavelet (db4) and determining a threshold through a loop to find the value where minimum error is achieved between the detailed coefficients of thresholded noisy signal and the original. The noisy and original signals are decomposed into five levels by discrete wavelet transform using the Daubechies wavelet (db4). For each level, a threshold value is found through a loop, and it is applied for the detailed coefficients of the noisy and original signals. The optimum threshold is chosen by taking the minimum error between the detailed coefficients of noisy signal and those for original signal. The soft thresholding is used to shrinkage the wavelet detailed coefficients of the noisy signal in following equation,

$$\omega_\lambda = \begin{cases} sgn(\omega)(|\omega| - \lambda), & |\omega| \geq \lambda \\ 0, & |\omega| > \lambda \end{cases}$$

$$\lambda = \sigma_i \sqrt{2 \log N_i / \log 2} \quad (4)$$

In this paper, our algorithm is introduced as shown in the following flowchart:

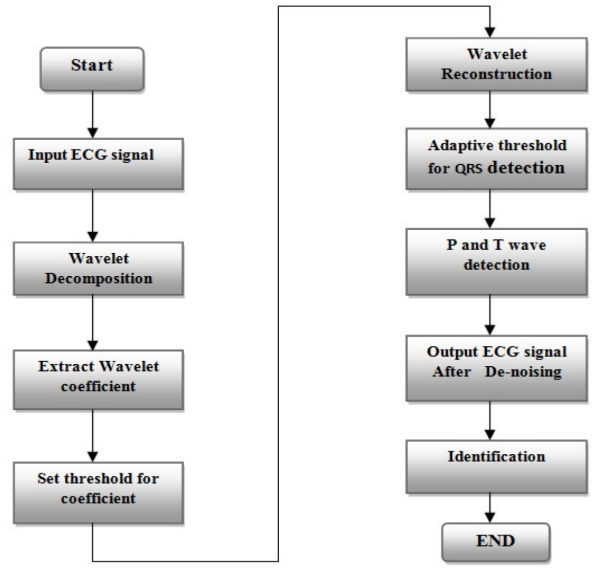

Fig.5.Flowchart of the de-noising process

Input real time ECG signal contains some amount of noise. Due to this, we apply wavelet decomposition to the signal which is decomposed signal into the specified level and gives detailed and approximated coefficients. Obtained coefficient gets extracted and after that, set the coefficients of threshold by using soft thresholding. After complete decomposition and thresholding, wavelet reconstruction is applied to the signal which is opposite to the decomposition. Then adaptive thresholding is done for QRS detection which detects the QRS peak properly and then detects P and T wave. After de-noising, it gives de-noise ECG signal that estimates required parameters to judge the quality of ECG signal obtained in real time.

4.2 Extended Kalman Filter

A classical problem in estimation theory is the estimation of the hidden states of a system with an underlying linear or nonlinear dynamic model that is observable through a set of measurements. The *Kalman filter* is one of these filters and it is proved to be the optimal filter in the *Minimum Mean Square Error* (MMSE) sense under some general constrains. But the conventional Kalman filter is only valid for linear models; while in practice, most practical systems are nonlinear. In order to extend the Kalman filter to nonlinear systems, a modified version of it is known as the *Extended Kalman Filter (EKF)* has been developed [22]. Due to the issue of nonlinearity, the EKF is no longer an optimal filter in the strict sense; but in practice, it has been shown that the EKF is a truly powerful adaptive filter.

For a discrete nonlinear system with the state vector x_k and observation vector y_k, the dynamic model may be formulated as follows:

$$\begin{cases} x_{k+1} = f(x_k, w_k, k) \\ y_k = f(x_k, v_k, k) \end{cases} \quad (5)$$

Where w_k and v_k are the process and measurement noises respectively with covariance matrices $Q_k = E\{w_k w_k^T\}$ and $R_k = E\{v_k v_k^T\}$. The initial state estimate of the state *x0* is defined as with $\bar{x}_0 = E\{x_0\}$ and $P_0 = E\{(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T\}$.

In order to use a Kalman filter formalism for this system, it is necessary to derive a linear approximation of (1) near a desired reference point $(\hat{x}_k, \hat{y}_k, \hat{v}_k)$. This approximation will lead to the following linear estimate:

$$\begin{cases} x_{k+1} \approx f(\hat{x}_k, \hat{w}_k, k) + A_k(x_k - \hat{x}_k) + F_k(w_k - \hat{w}_k) \\ y_k \approx g(\hat{x}_k, \hat{v}_k, k) + A_k(x_k - \hat{x}_k) + F_k(v_k - \hat{v}_k) \end{cases} \quad (6)$$

In order to implement the EKF, the time propagation is done using the original nonlinear equation while the Kalman filter gain and the covariance matrix are calculated from the linearized and the measurement propagation values. A synthetic ECG generator is based on a nonlinear dynamic model. This model has several parameters which makes it adaptable to many normal and abnormal ECG signals. The dynamic model consists of a three dimensional state equation which generates a trajectory with the coordinate (*x*, *y*, *z*).

$$\begin{aligned} \dot{x} &= \alpha x - \omega y \\ \dot{y} &= \alpha y + \omega x \end{aligned} \quad (7)$$

$$\dot{z} = \sum_{i \epsilon \{P,Q,R,S,T\}} a_i \, \mathrm{I}\Delta\theta_i \, exp\left(\frac{-\Delta\theta_i^2}{2b_i^2}\right) - (z - z_0)$$

The three dimensional trajectory which is generated from (7) consists of a circular limit cycle which is pushed up and down when it approaches one of the P, Q, R, S or T points. The projection of these trajectory points on the *z* axis gives a synthetic ECG signal.

Linearization of the Nonlinear Dynamic ECG Model based on the nonlinear synthetic model of (7). By using equation (7) and (6), linearize the nonlinear model. In order to model the effects of the mismatch of the dynamic model with a true ECG signal, it is necessary to encounter a process noise in the dynamic model. For this, an additive random Gaussian noise has been assumed in the dynamic model of (7). This small portion of noise, even for a truly noise-free dynamic model, gives more flexibility to the Kalman filter, and prevents it from converging to undesired limit cycles.

In this paper, an EKF was designed for the filtering of ECG signals. The EKF's dynamic model was based on a three dimensional nonlinear dynamic model previously introduced for the generation of synthetic ECG signals. This nonlinear model was linearized in order to be used in an EKF. The designed filter was later applied to the normal ECG signals, and the result shows the filter's capability in tracking and filtering noisy ECG signals. The proposed method can serve as a base for the design of a robust ECG filter with vast applications for low SNR ECG signals such as the noninvasive fetal cardiac signal extraction.

4.3 Extended Kalman Smoother

As with the Kalman Smoother, the Extended Kalman Smoother (EKS) uses the information of future observations to give better estimates of the current state. Due to this non-causal nature, the EKS is expected to have a better performance compared with the EKF [23]. The EKS algorithm basically consists of a forward EKF stage followed by a backward recursive smoothing stage. The EKS algorithm essentially consists of a forward EKF algorithm upto each time instant k, combined with a backward recursive smoothing algorithm using the observations beyond time instant k. Smoothing algorithms are usually divided into three types: fixed-interval, fixed-lag, and fixed-point. Fixed-interval smoothers use all the observations over a fixed interval to estimate the state of a system at all times in the same interval and are most commonly used for online processing. Here, the fixed-lag EKS is used since the filtering procedure is performed online on the whole length of ECG signal. Our system is real-time and hence proposes EKS methods; the fixed lag smoother is used for more appropriate filtering as compared with EKF.

4.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier or more commonly used for dimensionality reduction before later classification [20]. LDA works when the measurements made on independent variables for each observation are continuous quantities [17]. LDA explicitly attempts to model the difference between the classes of data. It provides the benefit of the fast extraction of feature from ECG signal. Equation of the Multiclass LDA is,

$$\Sigma_b - \frac{1}{c}\sum_{i=1}^{c}(\mu_i - \mu)(\mu_i - \mu)^T \quad (8)$$

where, μ is the mean of the class means; C is the eigen value; T is the threshold value.

Extracted features from filtering methods of ECG signal are further applied as an input to LDA classifier. Classifier is recognized as the difference between normal ECG signal and abnormal ECG signal and depending upon that, it gives QRS peaks, P and T peaks. LDA is used to classify the time-interval features that can approximately be extracted and compared with standard ECG cycle. The time-interval features are RR interval, QT interval, amplitude, shape of the waves etc. Wavelet transform, EKF and EKS methods are denoised and extract the feature of ECG signal. After that, LDA act as a classifier which classify features of ECG signal.

4. Results

In this section, ECG signals obtained in real time are sampled at 1 kHz in MATLAB. Fig.6 represents the ECG signal sampled per second at same frequency by using the formula for samples per second which is samples / sec = N/ Fs where, N is the length and Fs are sampling frequency. Here, we select the 15000 samples with 1 kHz sampling frequency. Fig.6. represents the signal in discrete continuous form called as original signal. If any drift is occurred in original signal, then it gets removed through the filtering process and generates the graph of base line elimination. Wavelet transform, EKF, and EKS filtering methods are used for de-noising ECG signal which eliminates noise and drift and graphs are generated which shows filtering performance of each method. Wavelet transform gives better performance of de-noising than EKF and EKS.

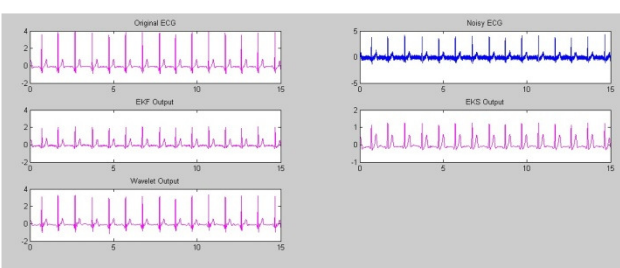

Fig.6. Performance of filtering Methods

Fig.7. shows filtered ECG signal which is classified by using LDA and extract the features of ECG signal. After that, the graph is generated called as LDA feature classification output. Graphs show the output of LDA-EKS, LDA-EKF, LDA-wavelet respectively. LDA-Wavelet gives us better feature extraction as compared to others. Wavelet transform gives the output of Wavelet detailed coefficients. Here Fig.9. shows eight level decomposition. Graph represents the output of wavelet detailed coefficient up to eight levels and Wavelet Approximation coefficient.

Table 2: Results of Males in Real time

Results of MALES							
Algorithms	TP	FP	FN	DER	PP (%)	Se (%)	ACC (%)
Wavelet Transform	69	5	2	0.064	93.91	98.58	95.42
Extended kalman filter	69	5	1	0.069	93.37	97.95	94.73
Extended kalman smoother	69	5	1	0.070	93.91	98.45	95.59

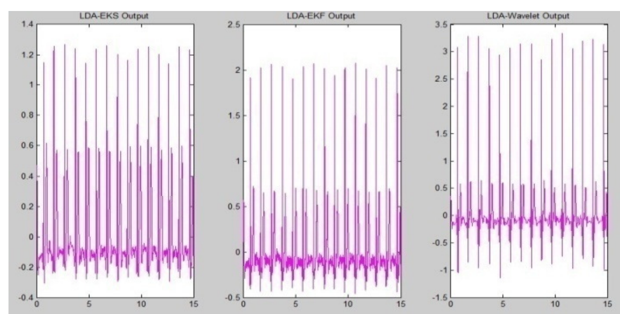

Fig.7. LDA Feature classification output

Table 3: Results of Females in Real time

Results of FEMALES							
Algorithms	TP	FP	FN	DER	PP (%)	Se (%)	ACC (%)
Wavelet Transform	67	6	2	0.076	91.37	97.06	97.20
Extended kalman filter	67	6	1	0.077	91.37	98.51	95.54
Extended kalman smoother	67	6	1	0.078	91.37	98.74	95.69

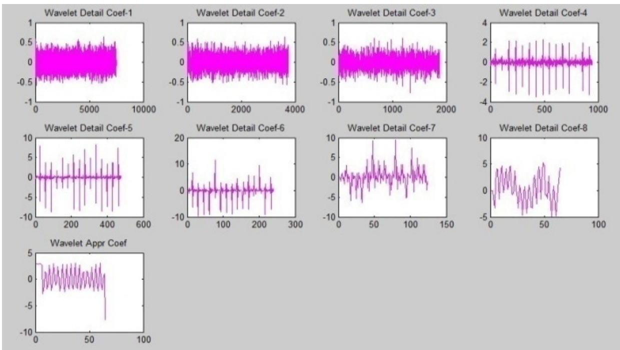

Fig.8. Wavelet Detailed Coefficients and Approximate Coefficients output

To evaluate the performance of the Wavelet transform and Linear Discriminant Analysis detection Algorithm, various performance indexes are introduced which are false negative (FN) that means failing to detect a true beat (actual QRS) and False positive (FP) represents false beat detection. By using FN and FP, the sensitivity (Se), Positive Prediction (PP) and Detected error can be calculated by using following equations,

$$Se = \frac{TP}{TP+FN} \quad (9)$$

$$PP = \frac{TP}{TP+FP} \quad (10)$$

$$DER = \frac{FP+FN}{Total\ QRS} \quad (11)$$

where true positive (TP) is the total number of QRS correctly detected by the algorithm.

Table 2 and 3 shows the average readings for 20 males and females respectively. For that, we have compared three algorithms i.e. wavelet transforms, EKF, EKS. Among all these, wavelet transform gives better performance.

5. Conclusions

The proposed embedded system design is used to detect the normal and abnormal problems generated in ECG signal measured in real time. System obtained is exact ECG signal in real time on Visual basic and value comes from the signal that is stored in drive on Personal Computer. After that, ECG signal parameters are correctly analyzed on MATLAB with the help of wavelet transform with LDA classifier which gives better performance than EKF and EKS algorithm. Wavelet Transform gives better Accuracy of 97.20% and Detection error ratio is 0.064, Positive Prediction 93.91% as compared with EKF and EKS. From the results, we have concluded that the real time system gives good results as MIT-BIH data. Proposed System is used for the home and hospitals for heart patients. It is cost effective.

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