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EXTRACTION METHODS OF FETAL ECG FROM MOTHER ECG SIGNAL IN PREGNANCY

Pushpa Devi Kushwaha[1], Rakesh Narvey[2] and D. K. Verma[3]

Student, Electrical Engineering Department, MITS Gwalior, M.P INDIA[1]

Asst. Professor Electrical Engineering Department, MITS Gwalior, M.P INDIA[2]

Electrical Engineering Department, MITS Gwalior, M.P INDIA[3]

Abstract: Fetal electrocardiogram (Fetal ECG) extraction is an interesting as well as a difficult problem in signal processing. The original FECG signal is nevertheless very complex and severely contaminated by external disturbances or noises. Identification of these cases during early pregnancy reduces risks by timely treatment or planned delivery. The non-invasive Fetal ECG (FECG) monitoring by means of abdominal surface electrodes provides valuable information about the cardiac electrical activity of fetus. It is very hard, even not impossible, to reliably extract the FECG from the abdominal signal using traditional techniques. The object of our work is to remove the noises in signals which are occurred due to power line interference, movement of patient etc. The extraction of fetal ECG is founded by Adaptive Noise Canceller, Principal Component Analysis, and Independent Component Analysis method. The procedure is applied to real multi-channel ECG recordings obtained from a pregnant woman. The experimental outcome demonstrates the more robust performance of the blind technique in this important biomedical application. After investigation of the results the ICA approach, proposed by us, has been shown to be superior for the extraction of fetal ECG compared to other methods. We using graphical user interface (GUI) which is a graphical display that enable a user to perform interactive tasks.

Keywords: ANC, Fetal ECG, PCA, ICA, GUI.

I INTRODUCTION

In non-invasive method, the Fetal ECG signals have a very low power relative to that of the Maternal ECG. In addition, there will be several sources of interference, which include intrinsic noise from a recorder, noise from electrode-skin contact, baseline drift (DC shift), 50/60 Hz noise etc. The situation is far worse during the uterine contractions of the mother. During these contractions, the ECG recordings will be corrupted by other electrophysiological signals called uterine electromyogram (EMG) or electrohysterogram (EHG), which are due to the uterine muscle rather than due to the heart. The response of the fetal heart to the uterine contractions is an important indicator of the Fetal health. As such a need arises to effectively monitoring the Fetal ECG during the uterine contractions. But monitoring the Fetal ECG during these contractions is a difficult task because of very poor SNR. The nature of the Fetal ECG is similar to that of mother ECG signal and is shown in Fig. 1. The ECG waveform is also called PQRST wave. The first waveform in the ECG-the P wave–is due to the trial contraction. The next waveform-QRS complex-is due to the ventricular contraction. The final waveform is the T wave which occurs as the heart prepares for the next heartbeat. The locations of P, Q, R, S and T components are indicated in the figure 1 [1].The three main characteristics that need to be obtained from the Fetal ECG extraction for useful diagnosis include

1. Fetal heart rate

2. Amplitude of the different waves

3. Duration of the waves.

But because of the non-invasive nature of measurement of the Fetal ECG, most of the signal processing algorithms detects only the R waves and the P and T waves will usually remain hidden. Also Fetal ECG extraction problem is not easily solved by conventional filtering techniques. Linear filtering in the Fourier domain fails since the spectral content of all the three components, Maternal ECG, Fetal ECG and noise are rather similar and overlap. FECG extraction and enhancement method requires the elimination of the MECG as well as optimal detection of the FECG. FECG can be used to classify arrhythmias, to study congenital heart disease and to observe fetal well being during growth retardation or (abnormal) twin pregnancy. Several methods for Maternal

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ECG cancellation of a FECG obtained via the abdominal wall have been reported.

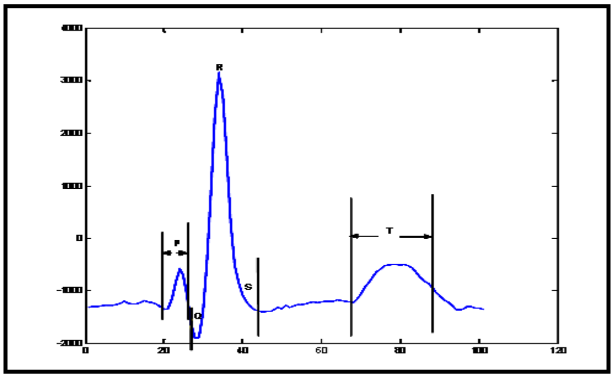

Fig. 1 Components of the ECG waveform

The major function of this electrical conduction system of the heart is to transmit electrical impulses from the SA node to the atria and ventricles, causing them to contract. Any disturbance in the regular rhythmic activity of the heart is termed arrhythmia. The voltage generated by atrial depolarization is the P wave. Ventricular depolarization is recorded as QRS complex. T waves correspond to the repolarization process. However, the effect of the atrial repolarization (Ta wave) is buried in the QRS complex because it normally occurs during ventricular depolarization.

A. Fetal ECG

Fetal ECG is the ECG of unborn child. When we take the ECG of mother it is the mixture of Maternal and Fetal ECG. It is very difficult to monitor the Fetal ECG.

The Fetal electrocardiogram (FECG) can be derived from the maternal abdominal ECG (AECG) and be used for the extraction of fetal heart rate (FHR), which indicates the cardiac condition of the fetus. The locations of leads for an 8-channel Maternal ECG acquisition system are shown in Figure 2 [5][16]. Maternal thorax ECG signals are sampled from thorax leads while abdominal ECG signals are obtained from abdominal leads.

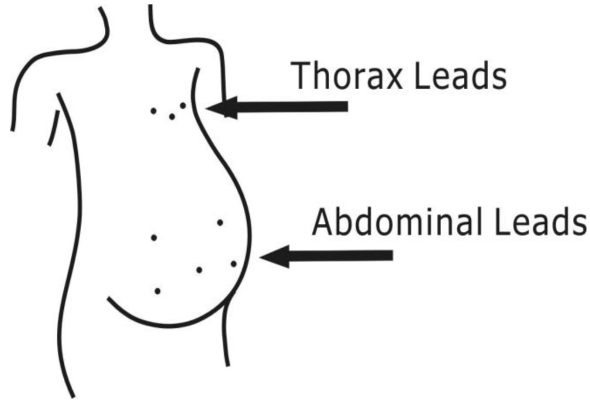

Fig. 2 Locations of lead sensors for 8-channel Maternal ECG acquisition system (including 5 abdominal leads and 3 thorax leads)

II MATERIALS AND METHODS

The methods which are used in this thesis are Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Adaptive Noise Canceller (ANC). PCA and ICA are the method of Blond source separation (BSS).
The term blind source separation (BSS) refers to a wide class of problems in signal and image processing [2] [3], where one needs to extract the underlying sources from a set of mixtures. Almost no prior knowledge about the sources, or about the mixing is know, hence the name blind. In practice, the sources can be one-dimensional (e.g. acoustic signals), two-dimensional (images) or three-dimensional (volumetric data). The mixing can be linear, nonlinear or convolutive in the latter case, the problem is referred to as blind deconvolution (in some applications, the terms blind system identification or blind equalization are more common) [4]. In many medical applications, the linear mixing model holds, hence the most common situation is when the mixtures are formed by superposition of sources with different scaling coefficients. These coefficients are usually referred to as mixing or crosstalk coefficients, and can be arranged into a mixing (crosstalk) matrix. The number of mixtures can be smaller, larger or equal to the number of sources.

A. ANC (Adaptive Noise Canceller)

ANC is possible when the noise or interference is not stationary and not necessarily a random process. The noise is uncorrelated with the signal. No information is available about the spectral characteristic of the signal and noise, which may also overlap significantly. A second source or recording site is available to obtain a reference signal that is strongly correlated with the noise but uncorrelated with the signal [10]. It is worth nothing that an adaptive filter acts as a fixed filter when the signal and noise are stationary. An adaptive filter can also act as a notch filter or a comb filter

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when the interference is periodic. It should be noted that all of the filter mentioned above are applicable only when the noise is additive.

B. PCA(Principal component analysis)

PCA (Principal component analysis) is a way of encoding second-order dependencies in the data by rotating the axis to correspond to the directions of maximum covariance. However, it does not address the high -order dependencies in the data. An equivalent formulation of PCA is to find a set of orthogonal components for the data [15].
More formally, PCA is a linear transformation that chooses a new coordinate system for the data such that the greatest variance by any projection of the data lies on the first axis (then called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a data while retaining those characteristics of the data that contribute most to its variance by eliminating the later principal components (by a more or less heuristic decision).

C. ICA (Independent Component Analysis)

Independent Component Analysis is a technique that recovers a set of independent signals from a set of measured signals [6]. It is assumed that each measured signal is a linear combination of each of the independent signals, and that there are an equal number of measured signals and independent signals. The following Fig. 3 shows an example of two independent signals and two measured signals that are linear combinations of the independent signals. We will refer to each of the original independent signals as Si and to each of the linearly combined mixed signals a X_i. X is a column vector of n measured signals [7].
Each measured signal can be expressed as a linear combination of the original independent signals:

$$X_i = a_1 S_1 + a_2 S_2 + \dots + a_n S_n \qquad 2.1$$

We can express the entire system of n measured signals as:

$$X = AS \qquad 2.2$$

Where each row of X is a set of readings
for each signal X_i; each row of S is an original signal S_i; and A is an n×n mixing matrix that generates X from S. The goal of ICA is, given X, find S and A.

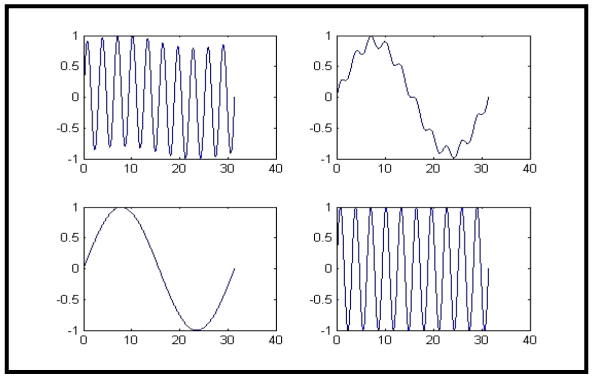

Fig. 3 These graphs show the measured signals X1 and X2 on the top, and the independent signals S1 and S2 on the bottom At first glance, this problem seems severely under constrained. However, ICA is looking for specific features in S that allows nearly unique solution to be found.

C (1) Maximum Entropy Method:

Maximum entropy is one of the methods in ICA [8]. This is an adaptive algorithm based on information theoretic approach and was suggested by Bell & Sejnowski [9]. The block diagram in Fig.4, explains the maximum entropy method for blind source separation. The demixer operates on the observed data X to produce an output Y = WX, which is an estimate of source S. The output Y is transformed into Z by passing it through a non-linearity G (.), which is invertible and monotonic. For a given non-linearity G (.), the maximum entropy method produces an estimate of source S by maximizing the entropy H (Z) with respect to W.

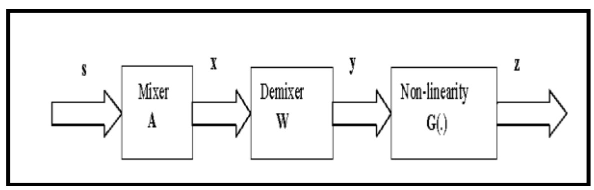

Fig. 4 Maximum Entropy Method

C (2) Maximum Entropy Algorithm to Extract Fetal ECG:

In order to make use of entropy to recover source signals it is clearly necessary to consider more than one recovered signal at a time so that the joint entropy of the set of recovered signals can be estimated. Having obtained a formal definition of entropy in terms of the recovered signals and the unmixing matrix W we need a method for finding that W which maximizes entropy of Y, and which therefore maximizes the independence of y.

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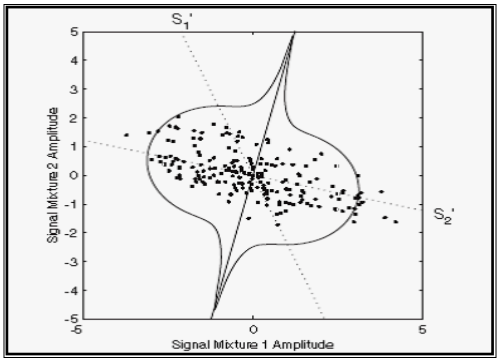

Fig. 5 Graph showing how joint entropy varies with weight vector orientation for two speech signal mixtures.

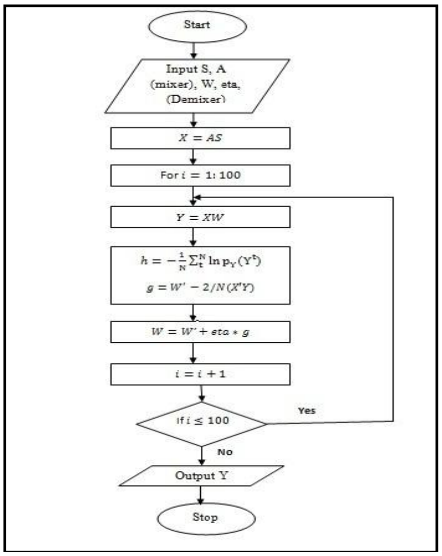

Fig. 6 Flow chart of maximum entropy method

Once again, the brute force exhaustive search method will do for now. In the case of two signals, this involves trying all possible orientations for the row vectors w_1^T and w_2^T in W = $[(w]_1, w_2)^T$. In Fig.5, W_2 is kept constant at the optimal orientation (i.e., orthogonal to S_1'). For illustrative purposes, and the value of h is plotted as W_1 is rotated through 360 degrees. As W_2 is constant, the changing value of h reflects the changing entropy associated with the signal y_1 extracted by W_1. As can be seen, entropy is maximal only when W_1 is at the correct orientation (i.e., orthogonal to S_2').Finally, note that if the model pdf p_s matches the pdf p_y of the extracted signals then maximizing the joint entropy of Y also maximizes the amount of mutual information between X and Y [9]. The flow chart of maximum entropy method is shown in Fig. 6. Where we find out the entropy of the matrix Y and then find out the gradient value g. Gradient find out the slope between vector S and W. New value of W is found by g. When W and transpose of S are orthogonal then entropy is maximal.

IV RESULTS

The database is original signal so we do not have any idea about the noise in these signals. For comparison we have to know about the actual signal which is the compare with the output of different methods. So we are using artificial signals for comparison. The artificially-generated data consisted of 4 different signals (sinusoid, square waves, saw-tooth and mixture of sin and cosine). Each is corrupted by additive random noise. For a better comparison and for computational needs, the data were normalized to zero mean and unit variance. The normalized source signals are shown in Fig. 7 with their corresponding histograms. The histogram's x-axis reflects the range of values in Y. The histogram's y-axis shows the number of elements that fall within the groups. When all corrupted signals are passed through all three methods (ANC, PCA, and ICA) the outputs of these methods are shown in Fig.8-10 As it can be clearly seen, the ICA's output's histogram is much more similar to the source signal's histogram than the PCA's and ANC'.

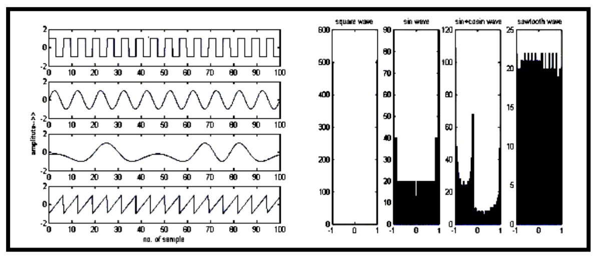

Fig. 7 Normalized Source Signals (left) and their Histograms (right)

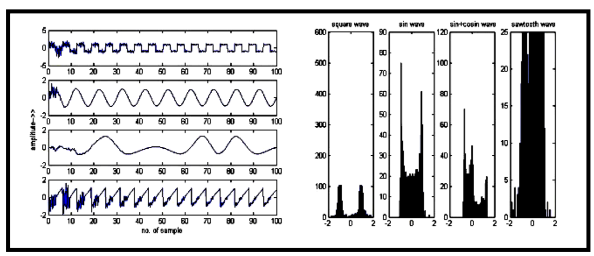

Fig. 8 Output of Adaptive Noise Canceller method (left) and their Histograms (right)

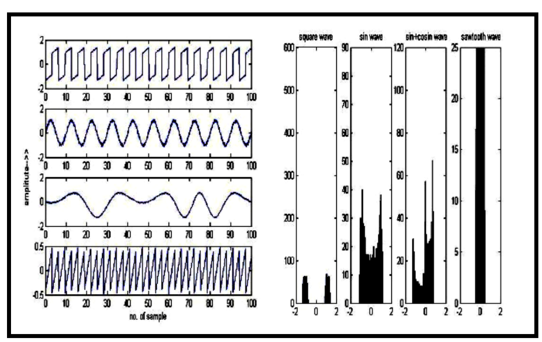

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Fig. 9 Output of Principal Component Analysis method (left) and their Histograms (right)

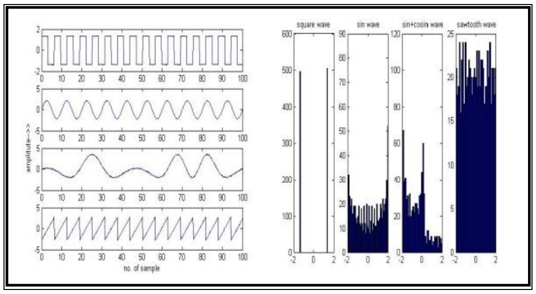

Fig. 10 Output of Independent Component Analysis method (left) and their Histograms (right)

A. Signal to Noise Ratio

Signal to noise ratio is another method to compare the all three methods. Signal to noise ratio is the ratio of power of signal to power of noise.

$$\boxed{SNR = \frac{Power\ of\ signal(dB)}{Power\ of\ noise(dB)}}$$

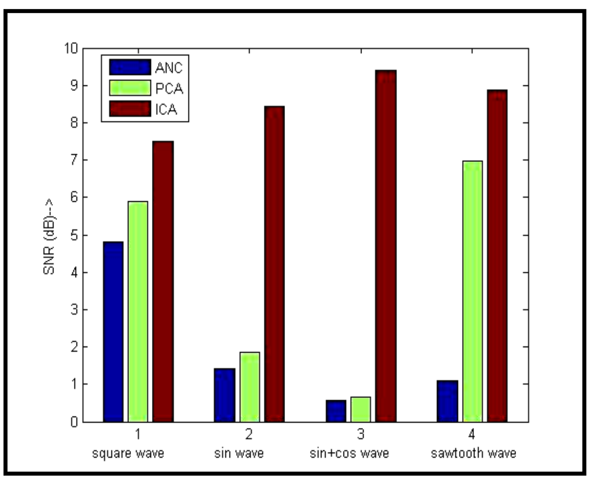

Fig. 11 SNR of different signals

Table 1 SNR of different signal from different algorithm

Methods/ Signal	Square	Sinusoidal	Sin+cos	Saw tooth
ANC	4.8070	1.4135	0.5703	1.117 0
PCA	5.8824	1.8686	0.6617	6.983 1
ICA	7.4935	8.4478	9.4032	8.864 0

Fig. 11 shows that the SNR of ICAs signal is high as compared to ANCs and PCAs signals. Which shows ICA is best method than ANC and PCA. Table 1 Shows the SNR of different signal from different algorithm.

B. Correlation Coefficients

The correlation coefficients between the source signals and the output of ANC, PCA and ICA respectively are plotted as shown in figure 12. It clearly shows that the correlation coefficients between the source signals and the output of ICA are nearly equal to one. However, they are low for the ANCs output and very low of PCAs output.

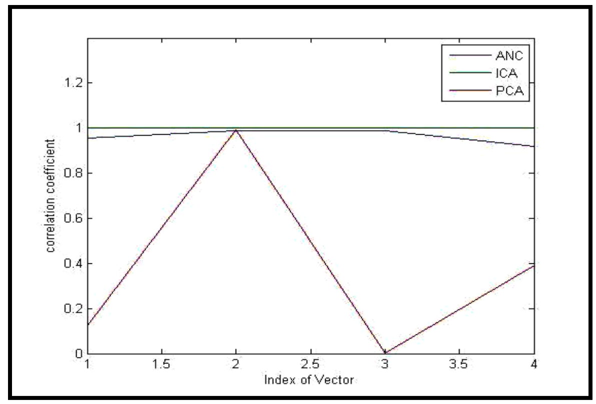

Fig 12 Plot of Correlation Coefficients between the Source Signals and the PCAs, ANCs and ICAs

C. Main Graphical User Interface (GUI)

The main GUI figure (Fig.13) shows the brief overview of whole thesis. It can be launched by typing 'main GUI' in the command window after making the MATLAB Path appropriate. It has different push buttons for opening other GUI figures namely 'Artifact Removal', 'Extraction of Fetal ECG' and 'Comparison'. These GUIs will be explained in detail in next sections.

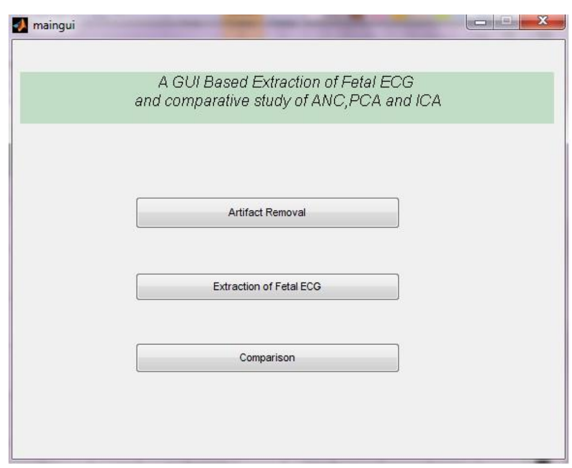

Fig. 13 Main GUI Figure – "Main GUI"

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C (1) GUI Extraction of Fetal ECG:

The GUI for "Extraction of Fetal ECG" is shown in Fig. 14. It can also be launched individually by typing 'extraction' in the command window. It has basically two popup menu box. One for extraction of Fetal ECG algorithm and another for heart rate calculation of signals. It has three push button namely 'Maternal', 'Fetal' and 'HR'. 'Maternal' button shows the mother's ECG and 'Fetal' button shows the Fetal ECG signal but firstly we have to select the algorithm form first popup menu (ANC, PCA and ICA). 'HR' button shows the different level of pan-Tompkins algorithm and heart rate of signal. Signals are selected from second popup menu (mother or Fetal)

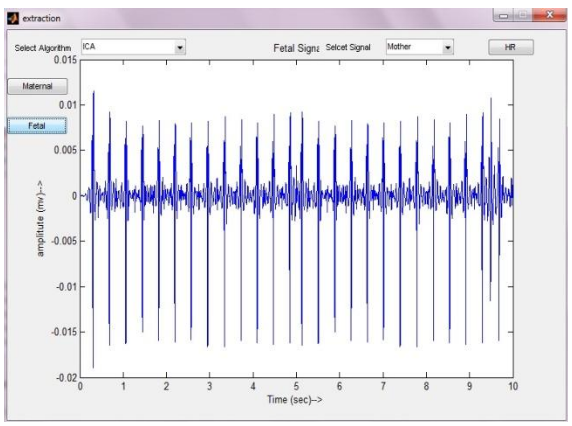

Fig. 14 GUI Figure – "Extraction of Fetal ECG"

C (2) GUI Figure – "Comparison" :

The GUI for "Comparison" is shown in Fig. 15. It can also be launched individually by typing 'comparegui' in the command window. This GUI used for comparison between ANC, PCA and ICA. It has basically one popup menu and four push button namely 'Signal', 'Histogram', 'SNR' and 'Correlation'. Popup menu box has different artificial signals which are used for comparison. 'Signal' button shows the original signal and output signal of all three algorithms. 'Histogram' shows the histogram of all output signal and original signal for comparison. 'SNR' button shows the bar graph of signal to noise ratio of all signals. 'Comparison' shows the graph of correlation between source signal and output of ANCs, PCAs and ICAs signals.

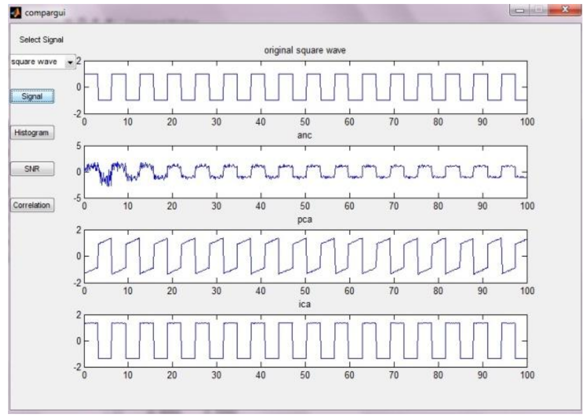

Fig. 15 GUI Figure – "Comparison"

V CONCLUSIONS

The experimental data is taken from MIT physio bank. It has different types of noises like power line interference, base line wonder, EMG noise etc. Besides the main goal obtained in this study, we believe that several findings are accomplished that can improve signal processing of ECG. These noises have been filtered using suitable filters. Power line interference (50 Hz) is a harmonic sinusoidal signal. Power line interference has been removed by adaptive filter. It is a best way to remove this noise. If we use notch filter then it can remove some data of actual signal. Base line wonder and EMG noise have low frequency signal so these has been removed through linear high pass filter. The extraction of Fetal ECG is done by the three methods, which are ANC, PCA and ICA. The data base is real signal so we do not know the nature of noise. So for comparison we used artificial signals and added random noise in these signals. After comparing these methods through histogram, SNR and correlation we found ICA is superior compared to ANC and PCAThe GUI provides the user friendly environment for whole thesis.

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BIOGRAPHY

Pushpa Devi Kushwaha student of Electrical Engineering Dept of MITS Gwalior. She is persuing her M.E in Measurement and Control from RGPV university Bhopal .Her B.Tech is in Electronics and Instrumentation Engineering from ITM, Gwalior. Her area of interest are Biomedical Instrumentation. She has done one International conference.