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Extraction of Fetal ECG from Abdominal Recordings Combining BSS-ICA & WT Techniques

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Abstract
The purpose of this project is to develop a noninvasive method to analyze fetal heart activity in uterus. Developing such a method is of high importance, since most of the current methods suffer from a high percentage of incorrect diagnoses giving false alarms for operational deliveries, and a small but significant percentage of undetected fetal distress. The work presented in this paper deals with Independent Component Analysis (ICA) approach to extract Fetal Electrocardiogram (FECG) from Abdominal ECG (AECG) recordings of pregnant woman from PhysioNet database. The noise in estimated FECG is removed by applying Wavelet Transform (WT). The accuracy of the implemented system is verified by comparing heart beat rate of extracted FECG with Reference Direct Fetal ECG record available in database. This study demonstrates that ICA can effectively distinguish the fetal independent components from maternal recordings.

Keywords:
BSS-ICA, Fetal ECG, Heart Beat rate, Wavelet Transform.

Introduction
The most common type of defects with which babies are born is related to heart; yearly 1 out of every 125 baby is born with some type of heart defects [1]. These heart defects can even lead to prenatal death also. So the fetal heart monitoring is an important part of prenatal care. Fetal distress is a common indication for the necessity of Caesarean delivery. It is described as a limited maternal-fetal respiratory exchange. When it happens an emergency is declared, since low oxygen levels can cause long-term disabilities & possible death. Fetal heart rate (FHR) value & regularity are considered parameters that indicate fetal distress. So it is very important to obtain highly accurate fetal heart rate estimation.

Today, the fetal monitoring is entirely based on the Fetal heart rate (FHR) monitoring assisting Doppler & Ultrasound/ Sonography techniques only & it does not incorporate the FECG waveform characteristics. The fetal ECG signal contains valuable information for characterizing the fetal heart rate variability and additional evaluation for cardiac functions. Cord compression, fetal heart block, fetal malposition, fetal arrhythmia such as Bradycardia, Tachycardia, Asphyxia, hypoxia, congenital heart disease and some other abnormal situations can also be detected by the FECG (Fetal cardiac waveforms) analysis [2].

A possible means for obtaining the FECG is using a fetal scalp electrode invasively. Although this is a widely used technique, it contains several potential risks and is possible only during labor [2]. Another non-invasive option for obtaining FECG is placing electrodes on maternal abdomen which can be done in any stage of pregnancy using dozens of electrodes [2]. The resulting abdominal ECG (AECG) contains mostly a high amplitude maternal ECG (MECG), a relatively small amplitude FECG with additional bioelectric undesired noises (generated by the muscles movements etc) as illustrated in Fig.1. To utilize the advantages of such a Non-invasive method, the numbers of signal processing techniques to retrieve the FECG from the non-invasive recordings are developed.

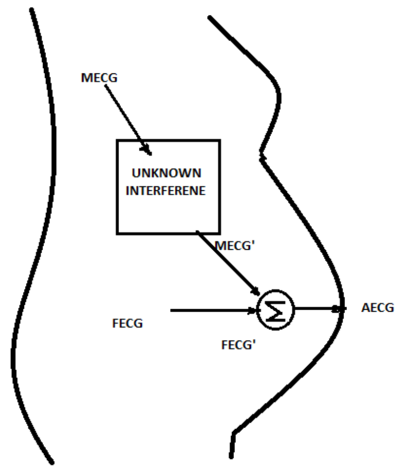

Figure 1: AECG & its components- Source of FECG

The use of fetal electrocardiography (FECG), although low-cost and simple to apply, has long been limited by poor signal quality. However, developments of signal analysis techniques have made FECG more accessible for clinical applications in general and HRV analysis in particular [1]. Lack of gold standard databases, Low FECG SNR and interferences like

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maternal electromyogram, baseline wander, power line interference, random electronic noise from the nearby instruments etc. are the limiting factors of non-invasive techniques. Moreover, except for during labor, fetal electrocardiography has not proved an effective tool for imaging specific structural defects. Rather, fetal electrocardiography has been confined to more global issues such as general ischemia due to specific fetal positioning that chokes the umbilical cord [2].

The reason for this limitation is that the noninvasive FECG is contaminated by fetal brain activity, myographic (muscle) signals (from both the mother and fetus), movement artifacts and multiple layers of different dielectric biological media through which the electrical signals must pass. So an efficient algorithm for extraction of fetal ECG from abdominal ECG providing an exact cardiograph (morphology) is required.

There are various methods for extracting FECG from AECG such as Adaptive filtering[3], wavelet Transform[4], Independent component Analysis, singular value decomposition (SVD)[5], Principle Component Analysis[6], Support Vector Machine and soft computing tools like Adaptive neural network[7], Genetic Algorithm, Adaptive Neuro Fuzzy Inference System[8] etc. All of them are having their own pros & cons [9].

Among the promising approaches for maternal & fetal ECG separation is using Blind Source Separation (BSS) in conjunction with Wavelet Transform (WT) [10]. BSS is the separation of a set of signals from a set of mixed signals with unknown mixing process. The process is called "blind" because of the minimum of priori information about the nature of separated sources. The method of independent components analysis (ICA) is the most common method to implement BSS, in which the separation process is based on the assumption about the difference between statistical characteristics and statistical independence of the separated sources [10]. Analysis of abdominal ECG by means of wavelet transform includes signal preprocessing to eliminate noise components and fetal ECG extraction [11]. Wavelet decomposition allows us to eliminate noise and suppress the main high-amplitude interference that dominates in abdominal signal – maternal ECG.

Methodology:

The general block diagram of the work presented in this paper is shown in Fig.2

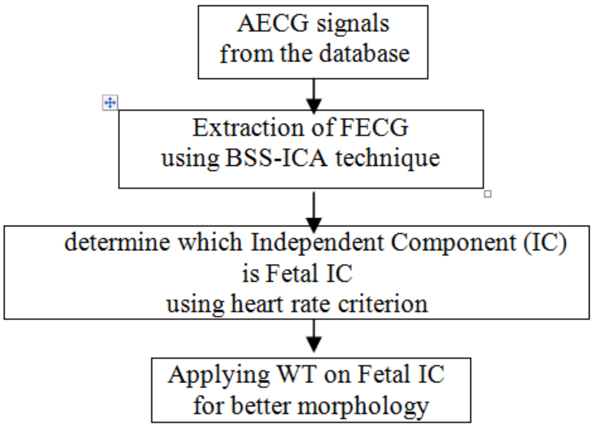

Figure 2: System block diagram

Electrocardiogram (ECG)

The generated electrical current through depolarization and repolarization of the heart can be measured by placing an array of electrodes on the body surface. The recorded signal is known as the electrocardiogram (ECG). Fig.3 shows a typical ECG signal.

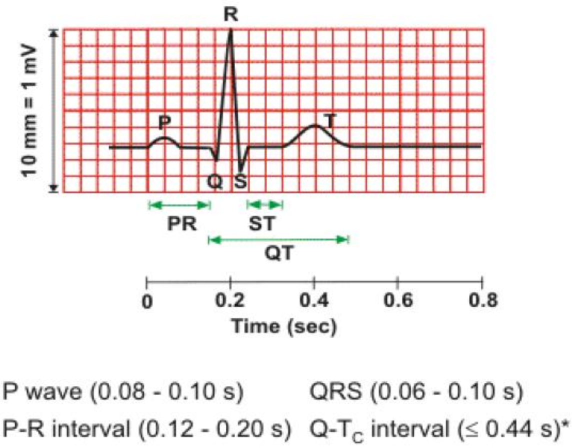

Figure 3: Typical ECG signal

As it is illustrated in Fig.3, ECG signal is composed of different waves each of which represents a particular activity of the heart.

Fetal Electrocardiograms (FECG)

Fetal heart is not the same as that of a newborn baby. Even their mechanical function is also different since the fetal heart doesn't need to pump blood to the lungs to collect oxygen. However, beat-to-beat electrical activity of fetal heart is rather similar [2]. FECG contains the same basic waveforms, the P wave, the QRS complex and the T wave, just like the adult ECG. But the values of the P-wave, the PR interval, the QRS complex, & the QT interval increase linearly with gestational age & in turn fetal heart beat rate is also dependent on gestational age. Normal embryo starts beating at under 85 bits per minute (bpm). It then increases from 110 to 185 bpm rapidly & stabilizes around 120-160 bpm.

Database

For the better analysis of the algorithm, the ECG acquired in real time scenario will be the best choice. Physionet offers free web access to a large collection of recorded physiologic signals in PhysioBank. Provided recordings in EDF format are already preprocessed by filtering for noise removal & constitutes an excellent material for testing (e.g. EDF annotations) of new FECG processing techniques. There are two databases relevant for this study.

i) The data from the Abdominal & Direct Fetal Electrocardiogram Database consists of 4-channel ECG recordings acquired from maternal abdomen & the reference direct FECG from the fetal head from 5 different women in labor. Among these 5 records, a record which has a better trace of fetal signal is selected for effective separation of MECG & FECG. One such a record is shown below in Fig.4. Only the 5000 samples of signal are shown in figure for better visualization.

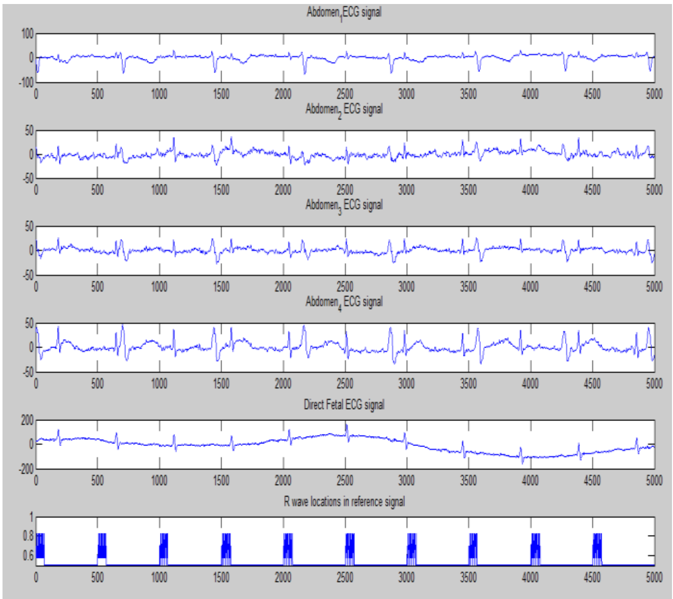

Figure 4: Abdominal ECG recordings & Reference Direct FECG with EDF annotations from Physionet Database

ii) The data from Non-invasive Fetal Electrocardiogram Database consists of a series of 55 multichannel abdominal recordings, taken from a single subject between 21 to 40 weeks of pregnancy. It includes 2 thoracic signals & 3 or 4 abdominal signals. The implemented algorithm is tested on 10 records having a better trace.

Implementation of BSS-ICA for FECG extraction:

When mixed signals overlap in both time & frequency domain, Blind Source Separation (BSS) is a promising approach. Separation of a set of mixed signals with unknown mixing process is termed as a BSS. Independent component analysis (ICA) is the most widely used technique in BSS [10]. The basic assumption of ICA is "statistical independence" of the sources. Different bioelectric current sources correspond to different bioelectric mechanisms, and so without loss of generality we can assume them to be statistically independent. General BSS model is shown below in Fig.5[12].

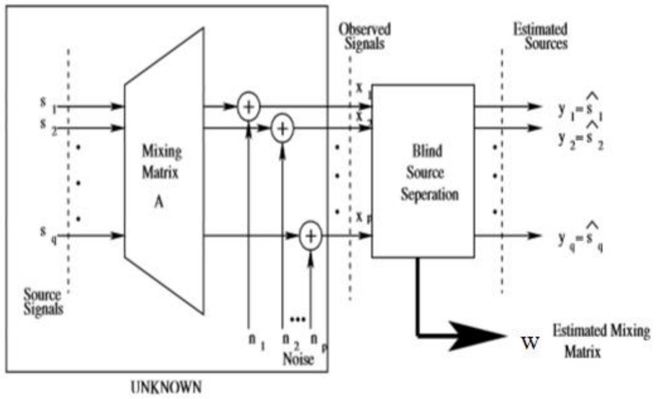

Figure 5: General BSS model

Analyzing Fig.5 with respect to Fig.1, Let

$$s(k) = [s_1(k), \ldots, s_q(k)]^T \in R^q \text{ --- (1)}$$

be the unknown independent bioelectric current sources of FECG, where k is the discrete time index and q is the number of sources &

$$x(k) = [x_1(k), \ldots, s_p(k)]^T \in R^p \text{ --- (2)}$$

be the abdominal signals recorded by the electrodes and p is the number of abdominal signals.

Then, the FECG extraction problem [i.e. estimation of s(k) only from x(k)] can be formulated as

$$x(k) = A\, s(k) + n(k) \quad \text{------ (3)}$$

where, matrix $A \in R^{pq}$ is the mixing matrix whose structure is determined by the body geometry, electrode placements and source positions.

$$n(k) = [n_1(k), \ldots, n_q(k)]^T \in R^p \text{ --- (4)}$$

represents the noise.

Equation (3) is the familiar instantaneous linear mixtures and thus the problem reduces to the estimation of the independent sources of fetal and maternal cardiac activity. The goal is to find out only from observations, x(k), an inverse matrix W such that the output

$$y(k) = W\, x(k) \quad \text{---- (5)}$$

is an estimate of the possible scaled and permutated source vector s. For estimating demixing matrix $W \in R^{pq}$, various ICA algorithms such as FASTICA, InfomaX, JADE, Bell & Sejnowski's algorithm, Comon's Pearson's ICA algorithm have been proposed.

ICA finds the independent components by maximizing the statistical independence of the estimated components [13],[14]. The two broadest definitions of independence for ICA are minimization of mutual information and maximization of non-Gaussianity. Typical algorithms for ICA use the centering and whitening, Eigen value decomposition, as preprocessing steps in order to simplify and reduce the complexity of the problem.

The system implemented in this paper uses FASTICA algorithm for ICA. FASTICA is an iterative algorithm which finds the direction for the weight vector by maximizing the nongaussianity of the projection for the data [15]. The function is the derivative of a non-quadratic of nonlinearity 'u' and constant 'a_1' defined as,

$$f_1(\mathrm{u}) = \tanh\,(a_1 * \mathrm{u}) \text{ --- } (6)$$

$$f_2(\mathrm{u}) = \mathrm{u} * \exp\,(\text{-u2/2}) \text{ -- } (7)$$

Fixed Point ICA (FPICA) algorithm for BSS-ICA is the main algorithm of FASTICA.

The original fixed-point ICA algorithm uses kurtosis and computations can be performed either in batch mode or in a semi-adaptive manner. It may use symmetric or deflation approach to update the columns of separating matrix W and to find the independent components one at a time. More recent versions are using hyperbolic tangent, exponential or cubic functions as a contrast function [16].

The update rule for the deflation method is given by

$$w^*(k) = \mathrm{C}^{-1}\,\mathrm{E}\{\mathrm{x}\,\mathrm{g}(\mathrm{w}(\mathrm{k}-1)^T\mathrm{x})\} - \mathrm{E}\{\,\mathrm{g}'(\mathrm{w}(\mathrm{k}-1)^T\mathrm{x})\}\,\mathrm{w}(\mathrm{k}-1) \text{ --- } (8)$$

And

$$\mathrm{w}(k) = w^*(k)/\sqrt{w^*(\mathrm{k}-1)^T\mathrm{C}w^*(k)} \text{ --- } (9)$$

where, g can be any suitable non-quadratic contrast function, with derivative g', and C is the covariance matrix of the mixtures, x. Then, every source would be presented by

$$w(k)^T x(t), \quad \mathrm{t}=1,2\ldots. \text{ ---}(10)$$

Analysis of FECG using Wavelet Transform (WT):

This includes signal processing to eliminate noise and extract Fetal ECG cardiograph to define diagnostic parameters in the signal. Abdominal ECG signal can be represented by multiresolution wavelet analysis as a sum of an approximation component a_m and the detail components d_j :

$$s(t) = a_m(t) + \sum_{j=1}^{m} \left(d_j\,(\mathrm{t})\right) \text{ --- } (11)$$

Where, m is the number of wavelet decomposition levels. The approximation coefficients correspond to the low-frequency components of ECG signal and the detail coefficients correspond to high frequency components of short duration. This property of wavelet decomposition allows us to remove noise from the abdominal signals and also to separate maternal and fetal ECG [17].

Noise appears at the detail levels of wavelet transform, therefore the task of noise suppression consists in detail coefficients processing. Coefficient values not exceeding a selected threshold level are replaced by zero. Appropriate threshold limit and threshold method (hard or soft) can be different at each level of wavelet decomposition.

The most essential stage of working with WT is to select proper mother wavelet. Selection of Wavelet is usually application dependent. The wavelet filter with scaling function more closely similar to the shape of the ECG signal achieves better detection [18]. In this study, we analyzed bior3.9, rbio3.9, coif5, sym8, db5, db6, db7 and db8 mother wavelets which are similar in shape to the ECG signal and have scaling function similar to ECG signal & finally selected coif5 for FECG noise removal.

Results & Discussion:

I. Result of ICA

Independent Component Analysis of the 4 abdominal ECG signals shown in Fig.4 was done using tanh function as a contrast function & the deflation approach to update columns of demixing matrix W. Whole signal with 300000 samples available in database were used for ICA. This analysis provided 4 Independent Components (ICs) as shown in Fig.6.

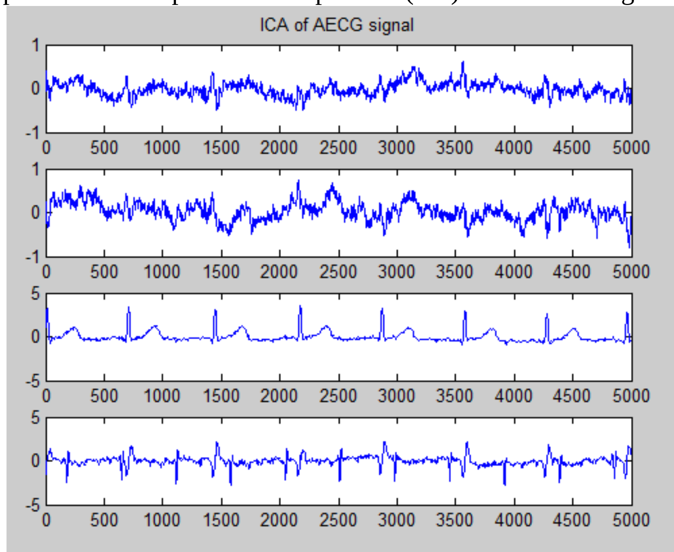

Figure 6: Four ICs obtained by ICA of AECG signals

These ICs consists of signals of Fetal & Maternal ECG components contaminated with little amount of interferences & other noise sources contaminated in AECG. We can say by observing IC that IC 3 & 4 represents the ECG components. Amongst them an ECG component with higher heart beat rate will represent the Fetal ECG [19].

II. Determining FECG component by computing Heart Beat Rate

For calculation of Heart Beat rate, first the R-peaks were detected in both ICs 3 & 4 using Librow's package. Then the number of R-peaks in 60 seconds which indicate the heart beat rate was computed. Similarly the heart beat rate of corresponding reference direct Fetal ECG signal available in database was computed. These heart rates were computed using formula of Fetal Heart Rate (FHR)

$$\mathrm{FHR} = 60 * \frac{Sampling\ \ Rate}{\text{Average Distance Between Peaks}}$$

It was found that heart beat rate of IC4 & reference signal was exactly same equal to 124 beats per minute (bpm). This clearly indicates that IC4 represents the FECG signal.

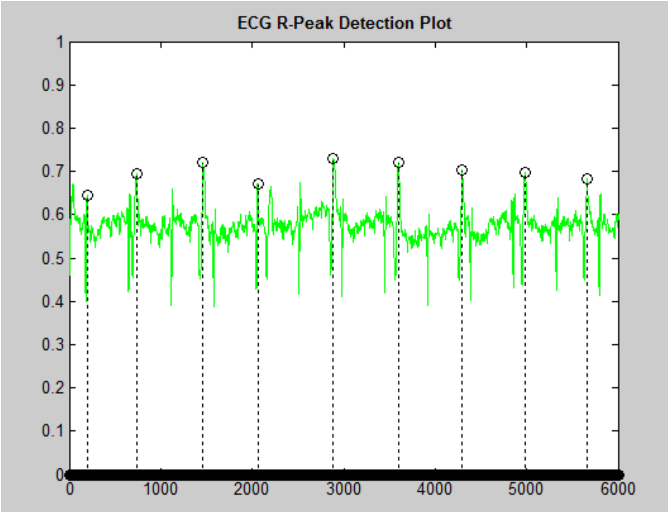

Figure 7: FECG signal extracted using ICA
With a plot of R-peaks

Since the Heart beat rate of extracted FECG & reference direct fetal ECG are exactly the same, we can say that ICA has extracted R-peaks in FECG from AECG in a very well manner. R-peaks detected in extracted FECG are shown in Fig. 7. For physicians to diagnose fetus's well being, we have to still enhance the extracted FECG for exact cardiograph of FECG.

III. Noise removal in extracted FECG applying WT

To suppress noise, the FECG component extracted using ICA was decomposed up to the 5th level with a "coiflet" wavelet of 5th order. The cardiograph was enhanced not completely but at few places in a very good manner as shown in Fig. 8.

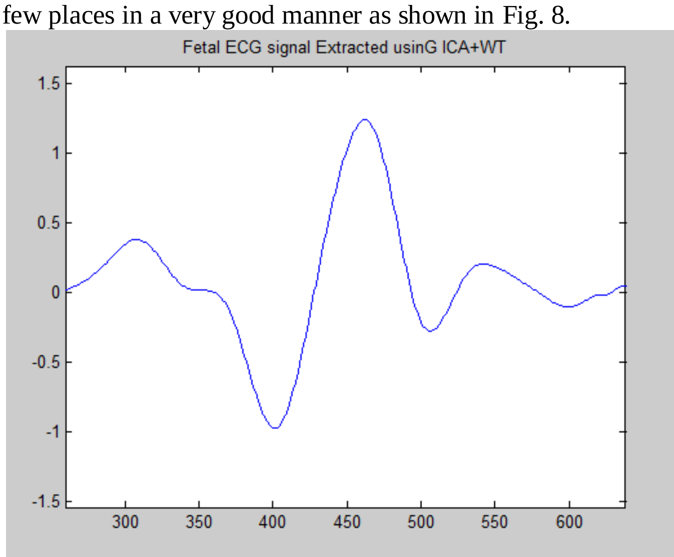

Figure 8: Enhanced FECG

Following figure 9 shows the overlapping plot of reference FECG, extracted FECG using ICA, & the extracted FECG combining ICA and WT. This plot proves that the implemented technique is able to extract FECG wisely.

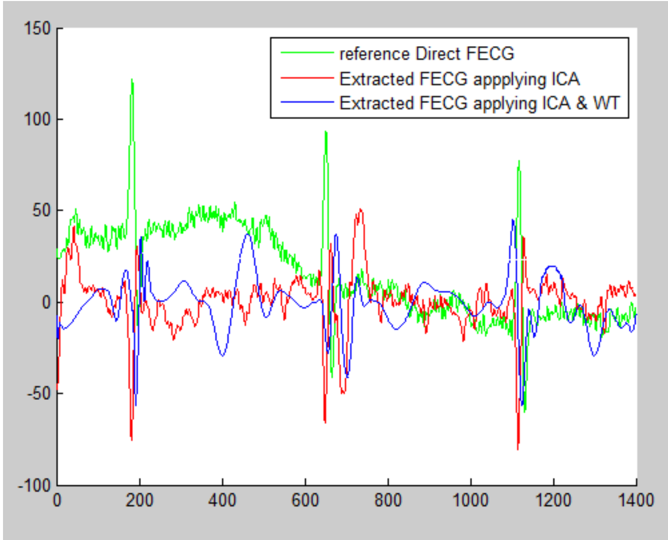

Figure8: plot for the Evaluation of performance of implemented technique

IV. FHR Calculation of other maternal recordings

The implemented technique is applied on the some abdominal non-invasive FECG recordings, taken from a single subject between 21 to 40 week pregnancy. The fetal heart beat rates computed after extracting FECG through it by above implemented technique are displayed below in table 1.

Signal from Database	FHR computed
ecgca998	110
ecgca968	108
ecgca896	136
ecgca886	110
ecgca880	187
ecgca840	183
ecgca776	185
ecgca771	172

Table 1: Estimated fetus's Heart Beat Rate
Using above implemented technique

Conclusion

In this paper a novel scheme BSS-ICA WT has been investigated for FECG extraction and enhancement. This work shows the ability of ICA in artifact removal from noisy data to extract FECG from maternal recordings. Also the results of WT application shows that R-peaks were detected in good manner, but all of the waves (P, Q, R, S & T) in cardiograph were not detected for the whole signal. The future work will be concentrating on different techniques for achieving the higher qualities of Fetal cardiograph & various diagnostic methods.

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