A New Fetal ECG Extraction Method Using its Skewness Value Which lies in Specific Range

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Abstract— **Every year, about one out of 125 babies born with some form of congenital heart defect. Therefore extraction of fetal electrocardiogram (FECG) from maternal skin electrode measurements will be raised as a prominent issue. Because of fetal heart farness from sensors, muscle contraction, instrumentation noise and etc, recorded signals from mother's abdomin is strongly distorted by noise. So desired signal (FECG) must be extracted purely. This problem can be modelled from the perspective of Blind Source Separation (BSS), almost all the BSS algorithms can be used to separate the fetal ECG. Since separating all the sources from a large number of sensor signals is not necessary, blind source extraction (BSE) methods may be a better choice.**

In this paper we proposed a lightweight algorithm, which extracts the fetal ECG with a preknowledge about its skewness. By using skewness, we defined a cost function by which we updated weight vector and through this we extracted fetal ECG as a desired signal. Experimental results show that the proposed method improved quality of extracted signal by increasing SNRsvd and SNRcor. Also computational cost required for extracting FECG was decreased.

Keywords: Source extraction; Independent component analysis (ICA); Blind source separation (BSS); Fetal electrocardiogram (FECG);

I. Introduction

Studies show that the most important source of mother's stress in pregnancy is because of fetus's health condition. Every year about eight out of one thousand babies are born with some form of congenital heart defects. The defect may be so slight that the baby appears healthy for many years after birth, or so important that his/her life is in immediate danger.

One way of knowing about the fetus's health condition in pregnancy is to consider the electrocardiographic signal recorded using non-invasive method. In this method, electrocardiograms are recorded from the mother's abdomen. Recorded signal is a combination of mother's electrocardiogram after travelling from the chest to abdomen, fetus's electrocardiogram and noise.

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Most cardiac defects have some manifestation in morphology of cardiac electrical signals, which are recorded by electrocardiography and are believed to contain much more information as compared with conventional sonographic methods. However, due to the low SNR of fetal electrocardiogram (ECG) recorded from the maternal body surface, we need an algorithm to extract fetal electrocardiogram among these recorded signals.

Recently, researchers found that the problem can be modelled as the blind source separation (BSS). Blind Source Separation (or, Independent Component Analysis, ICA), extracts all the source signals from a large number of observed sensor signals could take a long time and only a very few source signals are subjects of interest. For this application, another technique, blind (semi-blind) signal extraction (BSE) is a powerful candidate, since the BSE learning algorithms can extract a single source signal from a linear mixture of source signals. Therefore we are seeking three following targets:

- Extracting only desired signal (FECG) as an output
- Improving quality of extracted signal by increasing SNRsvd and SNRcor.
- Decreasing the computational time in order to making a real-time algorithm.

For achieving targets mentioned above we proposed an algorithm that using the range of skewness value of desired signal (FECG). Validity of our approach has been tested on real-world ECG data. The remainder of paper is organised as follow:

After a brief review of literatures in section 2, section 3 details the approach we proposed. Section 4 reports the experimental results and finally section 5 contains concluding remarks.

II. Literature review

Extensive studies have been conducted related to fetal ECG extraction. The discussion here is not intended to be comprehensive, but highlights some the most important one of them. In [1], adaptive filter technique was used to cancel the mother ECG and obtain the fetal ECG. They used two set of electrodes, one set place on abdomen of mother (primary inputs), and the other placed on the chest of the mother (reference inputs). Having these signals as an input to adaptive filter, the error signal can be made to represent the extracted fetal ECG. In [2], the method proposed by genetic algorithm that has a similar structure as method mentioned above. These methods are not robust enough to be used, because if the amplitude of background noise is greater than the fetal heart beat, the resulting error signal will not contain fetal ECG and when both the mother and fetal ECG overlapped in each other both methods will fail to extract the fetal ECG.

In [3], concept of singular energy vectors orthogonality was used to extract FECG form AECG. This method was not exploited widely in clinical environment, because the desired signal can be extracted successfully only if electrodes placed in a position that singular energy vectors of MECG and FECG are orthogonal to each other.

In [4], Barros and Cichocki proposed a semi-blind source separation algorithm to solve the fetal ECG extraction problem. This algorithm requires a priori information about the autocorrelation function of primary sources, to extracts the desired signal (FECG). They do not assume the sources to be statistically independent but they assume that sources have temporal structure and have different autocorrelation function. The main problem with this method is that if there is fetal heart rate variability, as in the case when the fetus is not healthy, the priori estimate of the autocorrelation function of the fetal ECG may not be appropriate.

Also in [5], Zhang and Zhang Yi proposed a blind source extraction (BSE) algorithm to extract a source signal from observed signals. Their algorithm needs a preknowledge about desired signal statistics. It means that by knowing the range in which the kurtosis value of the signals lies, the method can extract the desired signal.

In [13], Ming and Yu-lin proposed an algorithm that is combining of periodicity and kurtosis that proposed by barros [4], and Zhang [5], respectively. As mentioned above, in the case when the fetus is not healthy , the priori estimate of the autocorrelation function of the fetal ECG may not be appropriate.

In this paper we substituted kurtosis value with skewness value that persuaded us to applying some other modification to their method. These modifications will be explained in following section. By this substitution, we improved the quality of desired signal and increased SNRsvd and SNRcor. Also computational cost of proposed algorithm has been decreased.

III. PROPOSED ALGORITHM

Skewness measures the degree of asymmetry exhibited by the data. Since feal's heart beats more rapid than mother's and has a lower amplitude, therefore it's skewness absolute value is much lower than the mother's and is negative. By taking this fact in to consideration and doing comprehensive experiments on real and artificial world data we defined a range for fetus's skewness value. On the other hand, the skewness value of FECG generally lies in a specific range while the values of other source signals and noises do not belong to this range. In our method, by means of this range we separate FECG from other signal sources (MECG & noises) and extracted it purely. Accuracy of our range for fetal's skewness is checked with FECG's kurtosis range. In the following details of each steps of proposed algorithm are discussed.

A. Prerequisites

Assume a set of M sensors monitoring a phenomenon via the signals $x(n) = [x_1(n), x_2(n), ..., x_M(n)]^T$. Lets us also assume there are a number of N sources $s(n) = [s_1(n), s_2(n), ..., s_N(n)]^T$ that trigger the phenomenon observed by the sensors.

We will assume that the contribution of each factor is transmitted with insignificant delay to the observing sensors, i.e. instantaneously. In addition possible corruption by additive noise is considered insignificant. The following model connects the observed signals with the source signals via instantaneous mixing.

$$X = AS \tag{1}$$

, Where **A** is an unknown mixing matrix, X is abdominal signal matrix and S is source matrix that contains MECG(maternal ECG), FECG and noise. We will assume that the dimension of the observed signals **X** is larger than (or equal to) that of the source signals S**.** A fetal ECG extraction algorithm extracts a fetal ECG from the linearly mixed **X** by introducing an iterative process to find a vector **W** so that:

$$y = W^T X = W^T As \tag{2}$$

Generally, one of the drawbacks of BSS is that one cannot ensure in which order the sources will be estimated. So Blind Source Extraction (BSE) method is a better choice. Because in BSE, we can extract only desired signal. In first step, the measured sensor signals **X** have already followed by an n×n whitening filter **V** such that the components of $\tilde{x}(t) = Vx(t)$ are unit variance and uncorrelated. For convenience, in the following we assume that **X** is the prewhitened observed signals [7].

B. Skewness

In statistics, skewness is a measure of asymmetry, or more precisely the lack of symmetry. A data set is symmetric if it looks the same to the left and right of the center point (sample mean). Skewness can also be considered a third-moment. Because in whitened signal, *y* is a random variable of zero mean, the skewness can be defined as follows [6]:

$$skew(y) = \frac{E\{y^3\}}{E[y^2]^{3/2}} \quad . \tag{3}$$

In unsymmetrical sources skewness has positive or negative value. In positive skewness there are more observations below the mean than above it and in negative skewness there are a small number of low observations and a large number of high ones.

C. Algorithm

FECG signals are asymmetric in nature [6]. Since, unsymmetrical distributed sources can be extracted by employing skewness instead of kurtosis [7], proposed method is based on skewness. Because the duration and amplitude of FECG varies in a specific range, therefore its skewness value lies in specific range. So we suppose the skewness value of the FECG varies in [a,b] range. As a cost function, we employ equation (4) [8]:

$$J(W) = -\beta skew(y) \tag{4}$$

Note that $a \leq skew(y) \leq b$ and $\|W\| = 1$, where $\beta = sign(skew(y))$ and $y = W^T X$. With using a penalty function method [9], we rewrite the constrained cost function (4) as follow:

$$F(W,\sigma) = -\beta skew(y) + \sigma\{\max\{0, -(skew(y)-a)\}]^2 + [\max\{0, -(b-skew(y)\}]^2\} \tag{5}$$

Where, σ is penalty factor. The gradient of $F(W,\sigma)$ with respect to **W** can be considered as:

$$\frac{\partial F(W,\sigma)}{\partial W} = \begin{cases} -\beta \dfrac{\partial skew(y)}{\partial W}, if a \leq skew(y) \leq b \\ -\beta \dfrac{\partial skew(y)}{\partial W} - 2\sigma[a - skew(y)]\dfrac{\partial skew(y)}{\partial W}, if skew(y) \leq a \\ -\beta \dfrac{\partial skew(y)}{\partial W} + 2\sigma[skew(y) - b]\dfrac{\partial skew(y)}{\partial W}, if skew(y) \geq b \end{cases} \tag{6}$$

Where, $\dfrac{\partial skew(y)}{\partial W} = \dfrac{3m_3}{m_2^{5/2}}[\dfrac{m_2}{m_3}E\{y^2X\} - E\{yX\}]$, m_2 and m_3 are the second-order moment and the third-order moment of y respectively. Thus, a gradient descent learning algorithm is obtained as:

$$w(k+1) = w(k) - \mu\frac{\partial F(w(k),\sigma)}{\partial w(k)} = w(k) - \mu f(y(k))X(k)$$
$$w(k+1) = w(k+1)/\|w(k+1)\| \tag{7}$$

Where **k** indicate time index and

$$f(y(k)) = \begin{cases} -\beta g(y(k)), if a \leq \hat{skew}(y) \leq b \\ -[\beta + 2\sigma[a - \hat{skew}(y(k))]]g(y(k)), if\ \hat{skew}(y) \leq a \\ -[\beta + 2\sigma[b - \hat{skew}(y(k))]]g(y(k)), if\ \hat{skew}(y) \leq b \end{cases}$$

In which *g(y(k))* is obtained by:

$$g(y(k) = 3\frac{\hat{m}_3(k)}{\hat{m}_2^{5/2}(k)}[\frac{\hat{m}_2(k)}{\hat{m}_3(k)}y(k)^2 - y(k)] \tag{8}$$

And the following on-line estimation of m_p (p=2,3) and skew(*y*) are preformed respectively:

$$\hat{m}_p(y(k+1)) = (1-\eta(k)\hat{m}_p(k) + \eta(k)y^p(k)), (p=2,3)$$
$$\hat{skew}(y(k+1)) = \frac{\hat{m}_3(k+1)}{\hat{m}_2^{3/2}(k+1)} \tag{9}$$

Pseudo code of proposed algorithm is presented in Fig. 1.

*/*initialization phase*/*
Step1. Center the observed signals X and whiten them.
Step2. Initialize W and then compute $y = W^T X$.
*/*this is the phase in which skewness value converged to range [a, b]*/*
Step1.Compute skew(y)
if ($a \leq skew(y(k)) \leq b$) Then
$f(y(k)) = -\beta g(y(k))$
Else
if ($skew(y(k)) \leq a$) Then
$f(y(k)) = -[\beta + 2\sigma[a - skew(y(k))]]g(y(k))$
Else
if ($skew(y(k)) \geq b$) Then
$f(y(k)) = -[\beta + 2\sigma[b - skew(y(k))]]g(y(k))$
Step2. Update W, $skew(y(k))$ and moments according to (7) and (9) respectively.
Step3. Normalize W by $W/\|W\|$.
Step4. Compute $y = W^T X$
Step5. If ($skew(y(k)) \leq a \ \| \ skew(y(k)) \geq b$)
Go to step 1
Else
Plot the extracted FECG

Figure 1. pseduo code of proposed algorithm

IV. SIMULATION AND EXPERIMENTS ON REAL-WORLD DATA

We conducted comparison experiment to evaluate the performance of proposed fetal ECG extraction algorithm. The experiments were performed on a personal computer with 2 GHz Intel core 2 duo CPU and 1 GB RAM and the proposed algorithm was implemented in MATLAB environment. The performance measure is SNRsvd, SNRcor[10] and computer execution time to extract FECG. SNRsvd is a means to measure the difference between fetal signal energy (the first singular value) and noise energy (the sum of the rest singular values). Since the extracted signal only contains fetal component and uncorrelated noise, the more the value of SNRsvd was, higher quality of FECG extracted. Also SNRcor indicates the resemblance between each pulses of fetal ECG that is criterion to measure its periodicity. We compared the proposed algorithm with other similar methods presented in [3], [4], [5], [11]. For simulation experiments we used the well-known electrocardiogram (ECG) measured from a pregnant woman and distributed by De Moor (1997) [12]. The measured signals are 10 seconds long, which recorded with a 250 rate sampling per second. Parameters of proposed methods were set as follow:

$$a = -1, b = -0.4, \ \sigma = 2, \ \mu = 0.001, \ \eta = 0.9$$

Input data are shown in Fig. 2. The first five signals are recorded from the electrodes which placed on the abdomen of mother and the last three signals are from the chest of the mother.

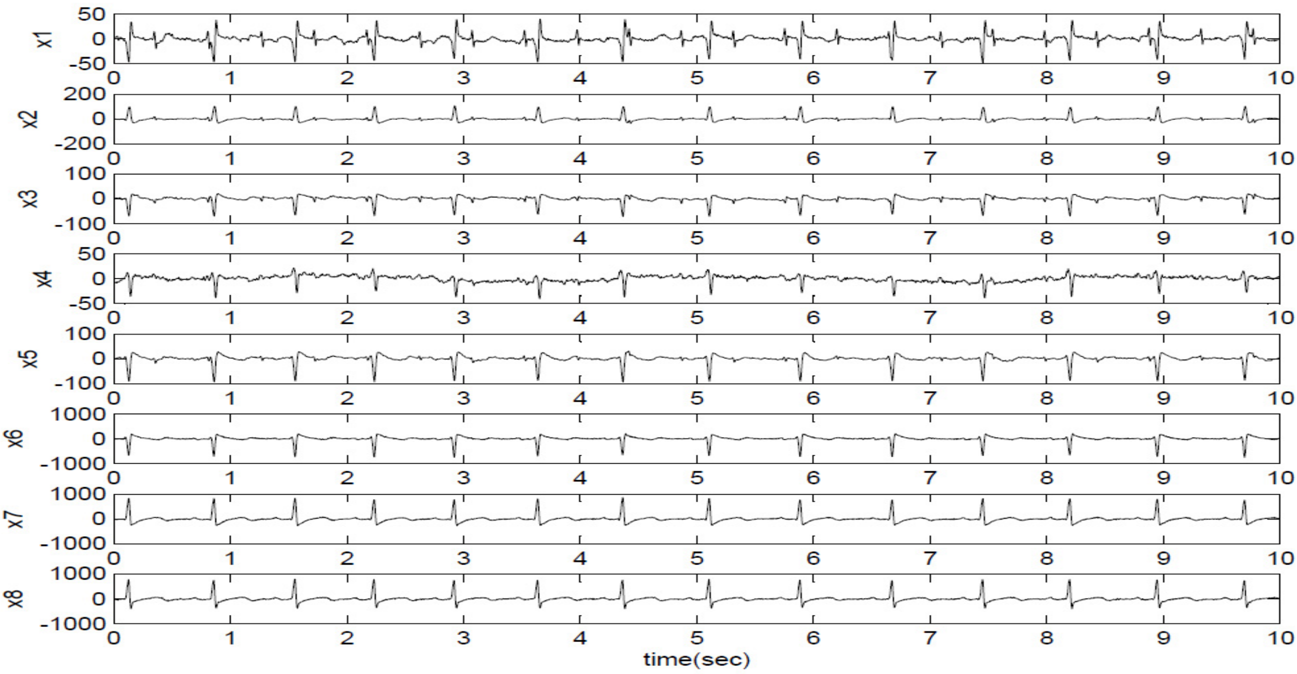

Figure 2. ECG input data

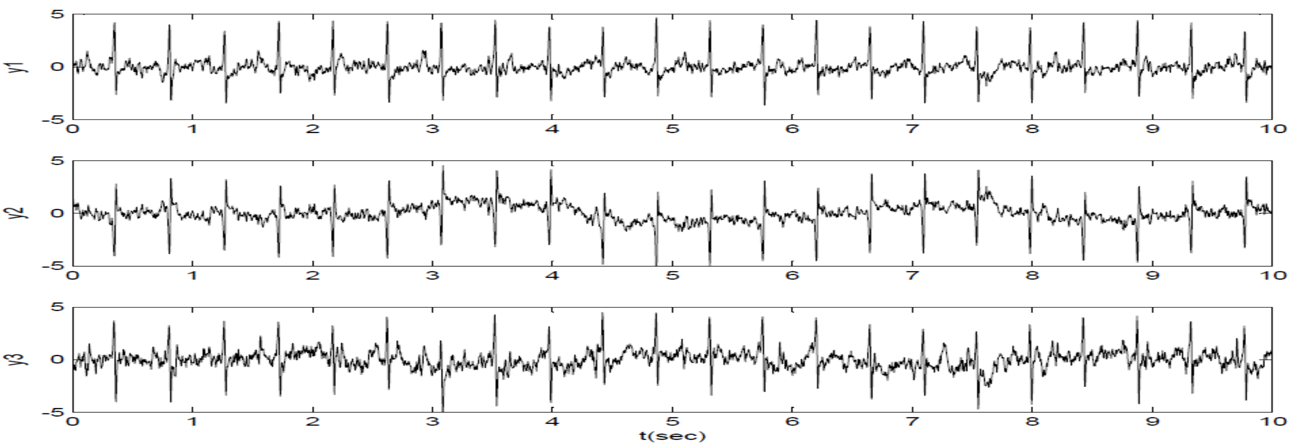

Figure 3. ouput FECG signals extracted from three methods below:

y1 is output of proposd algorithm, y2 is extracted by [4] and y3 is the output of [5] method

Table 1 summarizes comparison results among four other methods in terms of SNRsvd, SNRcor and execution time.

TABLE I. SUMMERISED COMPARISON RESULTS

	SNRsvd	SNRcor	Exe. time
Singular Value Decomposition[3]	0.3941	0.1373	8s
Independent Component Analysis [11]	0.4970	0.2048	12s
Blind Source Extraction [5]	0.9709	0.2659	4s
Semi-blind Source Seperation [4]	0.9896	0.2949	8s
Proposed algorithm	1.0089	0.2780	2s

As shown in Table 1, the proposed method has a better SNRsvd among all methods presented. Also SNRcor from our algorithm is better than the others except Semi-blind Source Separation. As it is obvious from the table 1, execution time of proposed method is superior to all the others. Fig. 3 plots the FECG extracted from proposed method and two other BSE algorithms [4], [5]. As illustrated in Fig. 3, PQRST waves of FECG signal extracted via proposed method is more obvious.

V. CONCLUSION

In this paper we proposed an efficient algorithm for extracting FECG signal. we have solved permutation problem in blind source separation (BSS) method by extracting desired source signal (FECG) only. This algorithm is generally could be a source extraction algorithm which extracts a desired source signals with a priori knowledge about the range in which its skewness value lies. Through the simulation on real-world data we proved that proposed method improve the quality of desired signal. Both SNRsvd and SNRcor of proposed algorithm are better than existing methods. Since for computing skewness we needed to calculate the 3^{rd} moment of FECG signal, computational execution time has been decreased in our algorithm.

Priori knowledge needed for proposed method obtained via statistical queries. But in similar methods like [5], for obtaining priori knowledge, a time delay constant must be estimated from sensor signals. If fetal is not healthy or sensor signals are impure, accuracy of time delay constant estimation is badly affected and resulted in undesired signal extraction. In contrast our algorithm does not have this drawback.

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