A Non-Invasive Method for Extraction of Fetal Heart Sound Signals using a Statistical Tool

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Abstract— In this paper, we present a novel approach to analyze and process the fetal heart sound signals (FHS). The proposed enhanced method extracts fetal heartbeat signals from the signal recorded by placing the mics on the mother's womb. The signals collected are processed by signal processing approach based on Blind Source Separation (BSS) technique. The approach shows that ICA can be efficiently used as a statistical tool for Blind Source Separation (BSS) and to process acoustic phonocardiograph. The experimental results obtained by the proposed technique are encouraging and shows the accurate extraction of the fetal heart sound signals. The output of the proposed method can be further used to analyze the heart rate of the fetus.

Keywords- *Independent Component Analysis (ICA), Blind Source Separation (BSS), Phonocardiography (PCG), Fetal Heart Sound (FHS)*

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I. INTRODUCTION

Congenital (inborn) heart defects are the most common birth defects and the leading cause of birth defect-related deaths. Most cardiac defects have some manifestation in the morphology of cardiac electrical signals, which are recorded by electrocardiography and are believed to contain much more information as compared with conventional ultrasonic sonographic methods. Therefore, the noninvasive study of fetal cardiac signals can provide an effective means of monitoring the well-being of the fetal heart and may be used for the early detection of cardiac abnormalities.

In previous studies, various methods have been developed for the processing and extraction of fetal electrocardiogram (ECG) signals recorded from the maternal body surface. However, due to the low signal-to-noise ratio of these signals, the application of fetal electrocardiography has been limited to heartbeat analysis and invasive ECG recordings during labor.

Phonocardiography is noninvasive technique analyzing the heartbeat rate. It involves picking up, through a highly sensitive microphone, sonic vibrations from the heart which are then converted into electrical energy and fed into a galvanometer, where they are recorded on paper. The procedure is most useful when there is evidence of heart murmurs or unusual heart sounds, such as gallops that are difficult to discern by the human ear. Most recordings are made through an externally applied microphone but intra-cardiac recordings, made through a phonocatheter, are also possible.

The basic idea behind the developed methods in extracting the fetal cardiograph is to use prior information about cardiac signals, such as their pseudo-periodic structure, to improve the performance of the currently existing techniques and to design novel filtering techniques that are customized for cardiac signals. Due to the overlap of the fetal signals and interferences/noises in different domains, the methods that use the information in only one of these domains do not usually succeed in extracting the fetal cardiograph. Therefore, the strong need is felt to develop methods that use the information from various domains, in order to improve the quality of the extracted signals.

The goal of this work was to improve the signal processing aspects of fetal cardiograph and to provide better insights of this problem, by developing new techniques for the modeling and filtering of fetal phonocardiographic (PCG) signals recorded through a highly sensitive microphone placed on the maternal abdomen.

II. METHODOLOGY

Firstly, the phonographs from the different subjects will be collected. Preprocessing will be carried out on the acoustic signals. The phonographic signals will be processed using the proposed algorithm. The implementation of the proposed algorithm will be carried out, and analysis and simulation of the fetal heart sound (FHS) will be demonstrated.

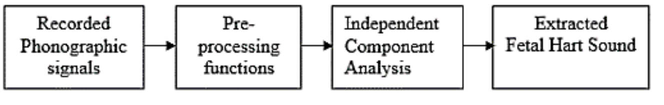

Figure 1. Fetal Heart Sound extraction Process.

The recorded phonocardiograph have a temporal structure that can be regarded as stationary for short timescales, although for longer time-scales, it is non-stationary due to the several reasons such as fetal moments. The algorithm can build which uses this temporal structure.

The difficulty of separating recorded phonocardiographic signals is due to the delays and reflections of the real environment. Those mixed signals are not instantaneous mixtures but convolutive mixtures [11]. We solve the problem of this convolution by applying a windowed Fourier transform. The time signals are transformed to time-frequency signals, and we apply

Molgedey and Schuster's decorrelation algorithm [10] to the signals of each frequency components. Molgedey and Schuster's decorrelation algorithm [10] cannot solve the ambiguity of permutation, and this can be a big problem when we reconstruct the time-frequency signal into separated time signals. We solve this ambiguity by using the time structure of the phonocardiograph signals. In particular, we use the envelope of each frequency signal to group the sources.

III. INDEPENDENT COMPONENT ANALYSIS

Recently, there has been an increasing interest in statistical models for learning data representations. A very popular method for this task is independent component analysis (ICA), the concept of which was initially proposed by Comon [6]. The ICA algorithm was initially proposed to solve the blind source separation (BSS) problem i.e. given only mixtures of a set of underlying sources; the task is to separate the mixed signals and retrieve the original sources [7]. Neither the mixing process nor the distribution of sources is known in the process. A simple mathematical representation of the ICA model is as follows.

Consider a simple linear model which consists of N sources of T samples i.e. Si = [Si(1), ...,Si(t),...,Si(T)]. The symbol there represents time, but it may represent some other parameter like space. M weighted mixtures of the sources are observed as X, where Xi = [Xi(1),... ,Xi(t),... ,Xi T)]. This can be represented as –

$$X = A\,S + n; \qquad (1)$$

Where

X= (X1, X2, X3………., XM); S= (S1, S2, S3………., SN) and n= (n1, n2, n3………., nk).

S and n represent the additive white Gaussian noise (AWGN). It is assumed that there are at least as many observations as sources i.e. M = N. The M × N matrix A is represented as –

$$A=\begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{M1} & \cdots & a_{MN} \end{bmatrix}; \qquad (2)$$

A relates X and S. A is called the mixing matrix. The estimation of the matrix S with knowledge of X is the linear source separation problem. This is schematically shown in Figure 2. The source separation problem cannot be solved if there is no knowledge of either A or S, apart from the observed mixed data X. If the mixing matrix A is known and the additive noise n is negligible, then the original sources can be estimated by evaluating the pseudo inverse of the matrix A, which is known as the unmixing matrix B, such that

$$BX = BAS = S \qquad (3)$$

For cases where the number of observations M equals the number of sources N (i.e. M = N), the mixing matrix A is a square matrix with full rank and B = A-1.

The necessary and sufficient condition for the pseudoinverse of A to exist is that it should be of full rank. When there are more observations than the sources (i.e. M > N), there exist many matrices B which satisfy the condition BA = I. Here the choice B depends on the components of S that we are interested in. When the number of observations is less than the number of sources (i.e. M < N), a solution does not exist unless further assumptions are made. On the other side of the problem, if there is no prior knowledge of the mixing matrix A, then the estimation of both A and S is known as a blind source separation (BSS) problem. A very popular technique for the solution of a BSS problem is independent component analysis [8]. Estimation of the underlying independent sources is the primary objective of the BSS problem. The problem defined in (3), under the assumption of negligible Gaussian noise n, is solvable with the following restrictions:

- The sources (i.e. the components of S) are statistically independent.
- At most, one of the sources is Gaussian distributed.
- The mixing matrix is of full rank.

From the above discussion, the following remarks can be made on ICA [10].

IV. ALGORITHM FOR CONVOLUTIVE MIXTURE

Basically, almost all ICA algorithms are good for separation of the instantaneous mixture of the non-Gaussian sources. But in real word situation, the mixing may not be instantaneous but convoluted.

Hence, the idea is to transform the mixed signals to the time-frequency domain, which is typically called a spectrogram. After that, we perform blind source separation for each frequency using an efficient version of EFICA [13]. improved version of the FastICA [8, 9] algorithm which is asymptotically efficient, i.e., its accuracy given by the residual error variance attains the Cramér-Rao lower bound. The error is thus as small as possible. The algorithm is tailored to achieve the efficiency when the probability distribution of the independent signal components belongs to the class of generalized Gaussian distributions with parameter α, denoted GG(α) [14]. Finally, we reconstruct the separated signals from the spectrograms.

We assume that observations are time independent convolutive mixtures, i.e.

$$x(t)=A*s(t); \qquad (4)$$

The whole convolutive Blind Source Separation algorithm can be summarized as follows; we have to assume here the two-channel input $x_1(t),\, and\ x_2(t)$,

1. Apply the windowed Fourier transform to the convoluted mixture signals $x_1(t)$, $and\ x_2(t)$, with proper window size.
2. For each $w_i\ of\ \ \tilde{x}_1(w,t_s) and\ \tilde{x}_2(w,t_s)$,
3. Apply an EFICA to get $\tilde{u}_{wi}(t_s) = B(w_i) * \tilde{x}_{wi}(t_s)$
4. Removing the ambiguity of amplitude with the inverse matrices$B(w)^{-1}\,\tilde{u}_{wi}(t_s)$.
5. Removing the ambiguity of permutation.

Reconstruct the separated signals by aligning these $\tilde{u}_{wi}(t_s)$ obtained for each frequency and apply the inverse Fourier transform.

V. Experimantal Results

The proposed technique is applied on the recorded phonocardiograph. The phonocardiograph used, is recoded using two single channel method in which one microphone was placed on the maternal abdomen (heart channel), and the other was directed into the open air to measure the external noise (external channel). The microphone signals were amplified using low noise high-precision amplified stages. The obtained line level audio signals were sampled at 16KHz, 16-bit resolution. Signal recorded from the heart channel, and the external channel is shown in Figure 2 and Figure 3 respectively. The output, i.e., extracted Fetal heart signal is shown in Figure 4 and the unwanted noise is shown in Figure 5.

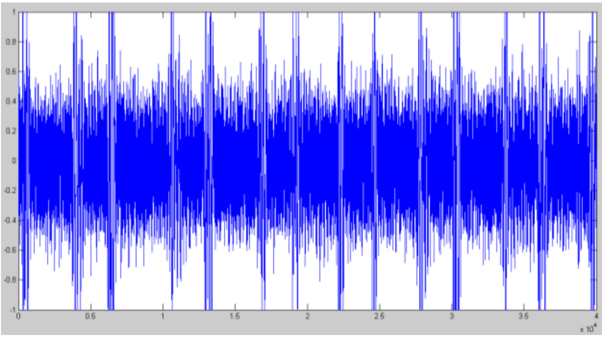

Figure 2. Signal recorded from the heart channel microphone

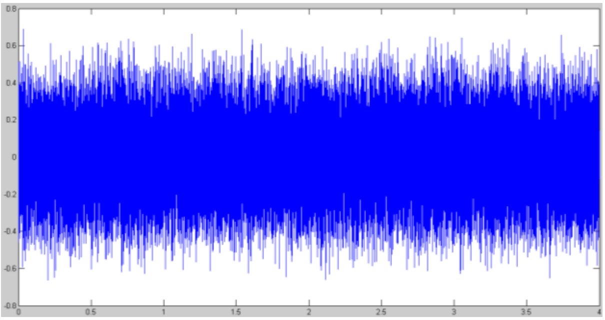

Figure 3. Signal recorded from external channel microphone

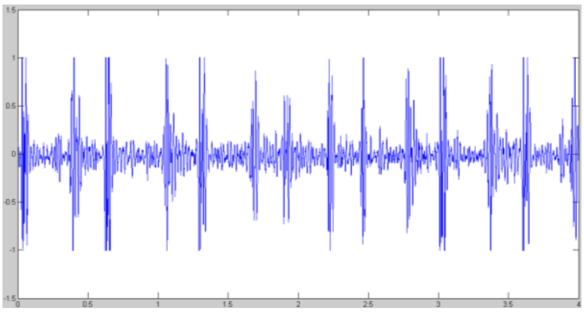

Figure 4. Extracted fetal phonocardiograph (fPCG)

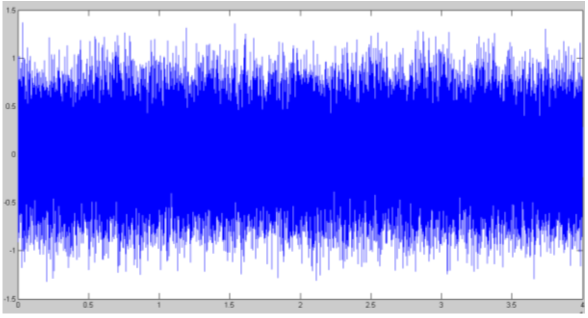

Figure 5. Extracted noise component

VI. Conclusion

The signals recorded from the maternal abdomen are not necessarily instantaneous mixtures but convolutive in nature. Hence, it is plausible to use the time-frequency analysis for sounds in natural environments. We have also taken care of the permutation and amplitude problem, which is the main ambiguity of any ICA technique. We have shown that this time-frequency based ICA technique can be used as an effective tool to monitor fetal heart rate.

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