Extraction of Fetal Heart Sound Signals using Independent Component Analysis

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Abstract— *In this paper a new method to extract the fetal heart sound signal from the abdominal phonocardiogram (PCG) is presented. Phonocardiography is a low-cost, passive, non-invasive way of recording heart sounds and murmurs. As this technique, consists of recording acoustic signal on the maternal abdominal surface; it is heavily loaded by noise and hence determination of the fetal heart rate (FHR) raises serious signal processing issues. In this paper we propose a method which uses a variant of fast independent component analysis (fastICA), EFICA; a Blind Source Separation (BSS) technique for the fetal PCG extraction.*

Keywords—*Independent Component Analysis, Blind Source Separation, Phonocardiography, FHR*

1. Introduction

Extracting the signals of interest from the real time observations of measurements is a fundamental signal processing challenge. Numerous applications which needs signal of interest recorded are often contaminated with the unwanted signals such as noise. Phonocardiography is one such area.

Phonocardiography is a continuous, low cost, non-invasive and simple way of detecting fetal heart rate (FHR). During pregnancy, the non-invasive measurement of beating activity of the fetal heart valves opening and closing can be done using an acoustic sensor placed on the mother's abdomen [1, 5].

The proper analysis of these signals allows the non-invasive way of detecting abnormalities in the fetal heart rate. The processing of phonocardiographic records aims the automated detection of the abnormalities present in the recorded signals [2, 3, 4].

Unfortunately, low amplitude fetal cardiac signals are very often contaminated by various factors, which can prohibit their automated analysis. These factors can be categorized as: [12]

- respiration sounds (lung mechanics),
- patient movements,
- small movements of the stethoscope ("shear noises"),
- acoustic damping through the bones and tissues, and
- external noises from the environment.

There are some other typical disturbances in the case of fetal phonocardiography [12]:

- acoustic damping of forewaters and maternal tissues,
- acoustic noises produced by the fetal movements,
- noises of the maternal digestive system, and
- sounds of maternal heart.

Most of the existing phonocardiographic processing methods concern only with the diagnostic analysis of heart sounds without an adequate emphasize on the denoising of the records. Existing methods usually apply digital band-pass filters (most commonly IIR-filters of FFT-based filtering) as a simple denoising method. The cut-off frequencies of the filters are determined by empirical observations, and commonly the passed band lies between 30 and 200 Hz [3, 4, 5]. The goal of this paper is to develop a method of extraction of fetal phonocardiograph using ICA in Time and frequency domain.

This paper is organized as follows: in section 2, discusses the methodology, then we describe some basics of ICA in section 3, we propose an algorithm for extraction of fetal PCG in 4, and, in section 5 some results are shown. Finally, we give concluding remarks in section 6.

2. Methodology

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.

3. 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. $S_i = [S_i(1), ..., S_i(t), ..., S_i(T)]$. 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 $X_i = [X_i(1), ..., X_i(t), ..., X_i\ T)]$. This can be represented as –

$$X = A\,S + n; \tag{1}$$

Where
$X = (X_1, X_2, X_3 \ldots\ldots\ldots, X_M)$; $S = (S_1, S_2, S_3 \ldots\ldots\ldots, S_N)$ and $n = (n_1, n_2, n_3 \ldots\ldots\ldots, n_k)$.

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 –

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

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

$$BX = BAS = S \tag{3}$$

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 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].

4. Algorithm for Convoluted Mixtures

Basically almost all ICA algorithms are good for separation of the instantaneous mixture of the non guassian 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 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.

$$x(t) = A * s(t); \tag{4}$$

The whole convolutive Blind Source Separation algorithm can be summarized as follows; we have assuming 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.
6. Reconstruct the separated signals by aligning these $\tilde{u}_{wi}(t_s)$ obtained for each frequency and apply the inverse Fourier transform.

5. Results

We have applied the above BSS technique 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 16 KHz, 16 bit resolution.

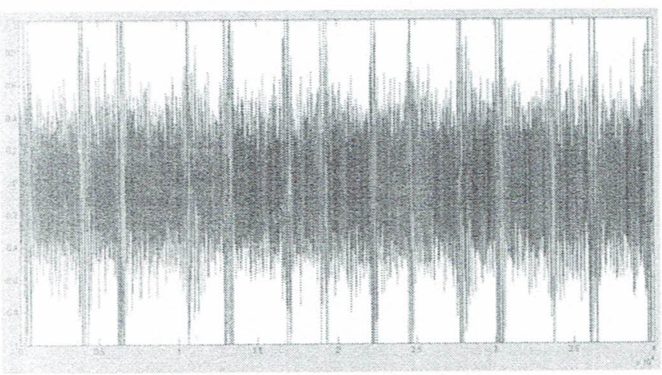

Fig. 1. Signal recorded from the heart channel microphone

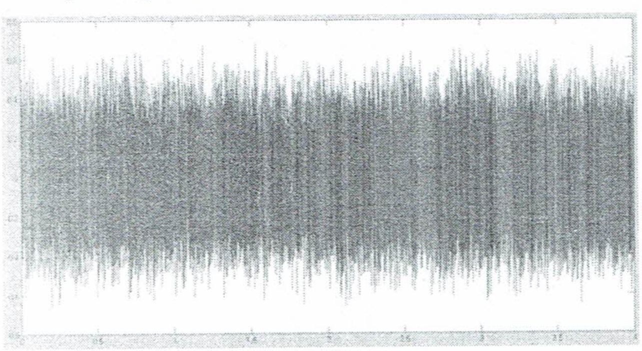

Fig. 2. Signal recorded from external channel microphone

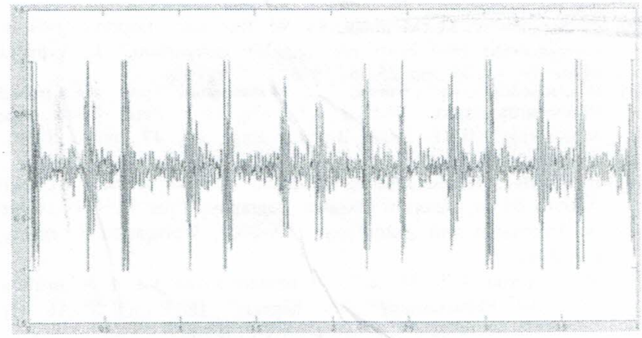

Fig. 3. Extracted fetal phonocardiograph (fPCG)

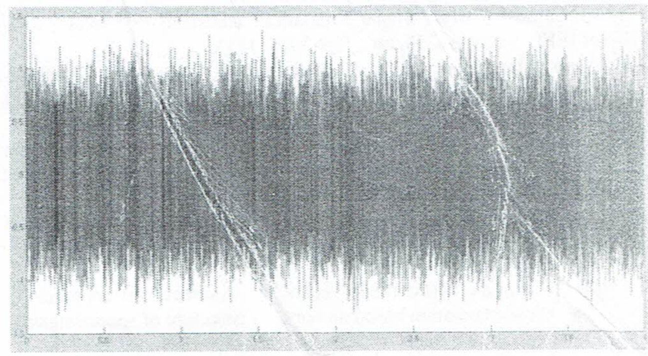

Fig. 4. Extracted noise component

6. 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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