Online Non-Invasive Fetal Sound Analysis

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Abstract

A method is presented to non-invasively separate the fetal phonocardiograms (FPCG) of the fetuses in a multiple fetus pregnancy. The method uses a device like a stethoscope. We assume that the phonocardiograms of the fetuses are statistically independent. Results of simulations are included in the paper.

1. Introduction

A multiple gestation is a pregnancy in which a woman carries more than one fetus. In the past two decades, the number of multiple births in the United States has jumped dramatically. The number of twin births has increased 74 percent, and the number of triplets or more has increased fivefold, according to the National Center for Health Statistics. Today, about 3 percent of babies in this country are born in sets of two, three or more, and about 95 percent of these multiple births are twins. The rising number of multiple gestations is a concern because women who are expecting more than one baby are at increased risk of certain pregnancy complications, including preterm delivery. Some of the complications associated with multiple gestations can be minimized if they are detected and diagnosed early [13].

The embryonic heart starts beating 22 days after conception. The heart at this stage is too small to hear, even with amplification. By the 9th to 10th week after the last menstrual period of the expecting mother, one might be able to hear the fetus’ heartbeat. By the 12th week, the heartbeat can usually be heard consistently, using a Doppler instrument for amplification [9].

Although the human ear is unequalled in detecting sounds over a particular frequency range, the spectrum occupied by fetal heart sounds is on the threshold of audibility. This aural processing has always caused problems relating to degree and accuracy of fetal experiments and results. Section 6 concludes the paper with discussion about future work.

2. Blind Source Separation

Blind Source Separation (BSS) denotes observing mixtures of independent sources, and by making use of auscultation [14]. Electronically processing the fetal phonocardiogram (FPCG) presents a way of avoiding these problems. The greater low frequency sensitivity of the phonocardiographic transducer captures all the acoustic information generated by the fetal heart. Then, additional visual examination of the FPCG provides an effective way of determining temporal measures of fetal cardiac function. The FPCG allows the measurement of the instantaneous fetal heart rate (FHR), beat-to-beat differences and duration of systolic and diastolic phases. These measures are sensitive indicators of cardiac function, reflecting fetal well being. With the record of various critical cardiac activities readily available, some abnormalities of the fetal heart can be detected in the early stages of the pregnancy. However, a major problem arises in the event of a multiple gestation. When more than one fetus is present in a mother’s womb, the acoustic transducer (acoustic or electronic stethoscope) captures multiple FPCGs. It becomes difficult to clearly discern the sound from each fetus in this case.

An intuitive assumption can greatly ameliorate this problem. In a multi-fetal pregnancy we assume that the phonocardiograms of the fetuses are statistically independent. However, the acoustic energy produced by each fetus is summed up at the transducer, which records a mixture of FPCGs. Moreover, the acoustic signal transit times from the fetuses to a transducer are not equal. Since the heart activities of the fetuses are assumed to be statistically independent, we consider the application of blind source separation (BSS) techniques to separate the individual phonocardiograms from their mixtures. We demonstrate that a modified BSS algorithm can successfully separate the FPCGs in multi-fetal pregnancies. The paper is divided as follows. Section 2 gives a brief introduction to BSS. Section 3 discusses a more general delayed source separation algorithm. Section 4 presents an algorithm to implement delayed source separation in near-real time. Section 5 discusses experiments and results. Section 6 concludes the paper with discussion about future work.

x = As, \(x \in \mathbb{R}^n, s \in \mathbb{R}^m, A \in \mathbb{R}^{n \times m}\) (1)
where $A$ is the mixing matrix. The $m$ components of the vector $s$ are the acoustic signals from $m$ fetuses, and we assume that these components are statistically independent and have probability distributions that are not Gaussian except for at most one component. To obtain a unique separation of sources given such the set of mixtures $x$, we assume that $m$, the number of sources, is less than or equal to $n$, the number of observations. The goal of BSS is to learn a separation matrix $W$ that can be applied to the observations to obtain an estimate $v$ of the original sources with

$$v = Wx \quad (2)$$

Learning $W$ by observing $x$ only requires making use of higher order statistics [15]. Typically, the separating matrix $W$ is calculated iteratively by optimizing some cost function of the estimate $v$. Presently reported approaches to this problem can be divided into two categories. One category makes use of these statistics implicitly through the non-linearity of neurons in a neural network [11] [12] [6] [7] [10] [12] [16], and the other category makes use of higher order statistics explicitly [4] [8] [17] [19]. However, for separation of fetal phonocardiograms, instantaneous mixing is not a realistic assumption. This is because the sounds originating from fetal hearts take different amounts of time to travel to the transducers at the mother’s abdomen. Hence each FPCG incurs a different delay before mixing at the transducer. We show that when there are different propagation delays from the sources (fetal hearts) to the sensors (transducers at the mother’s body), conventional methods for BSS produce unsatisfactory separation.

A method, called Blind Delayed Source Separation (BDSS), is presented in the next section that successfully separates delayed sources from their mixtures. BDSS can be used to separate twin FPCGs in a multiple gestation. It requires knowledge of observations over a time range, and it repeatedly sweeps over the observations to estimate the weight matrix $W$ and the propagation delays.

### 3. A General Model for Delayed Sources

Torkkola [18] showed that mixtures of delayed sources could be separated by a feedback architecture using adaptive delays. This is similar to the architecture that was previously proposed by Jutten [10] to which Platt and Faggin [16] later added adaptive delays. The delayed source model, that is closer to many real life-mixing situations, is one that incorporates delays incurred by each source while reaching the sensors. Such a mixing model is given by

$$x_1(t) = a_{11}s_1(t - d_{11}) + a_{12}s_2(t - d_{12})$$

$$x_2(t) = a_{21}s_1(t - d_{21}) + a_{22}s_2(t - d_{22}) \quad (3)$$

To separate the sources from mixtures modeled by (3), we introduce differential delays and recover delayed versions of the original sources. The network used to separate the sources is shown in fig. 1. The network computes the $u_i(t)$, given by

$$u_1(t) = w_1x_1(t) + w_{12}u_2(t - (d_{12} - d_{21})) + w_{01}$$

$$u_2(t) = w_2x_2(t) + w_{21}u_1(t - (d_{21} - d_{12})) + w_{02} \quad (4)$$

which are the inputs to the nonlinearities, where

$$y_1(t) = g(u_1(t)) = 1/(1 + \exp(-u_1(t)))$$

$$y_2(t) = g(u_2(t)) = 1/(1 + \exp(-u_2(t))) \quad (5)$$

The network shown in fig. 1 updates its parameters by minimizing the mutual information [15] between its outputs $y_1$ and $y_2$. When the mutual information between the outputs becomes zero, they become statistically independent, and we obtain estimates of the delayed original sources $s_1(t - d_{11})$ and $s_2(t - d_{22})$. The non-linearity before the outputs $y_1$ and $y_2$ exploits the higher order statistics of the estimates implicitly. By decorrelating the higher order statistics between the estimates we tend to make them statistically independent of each other, thus achieving our objective.

If we define

$$b_1 = d_{21} - d_{11}, \quad b_2 = d_{12} - d_{22} \quad (6)$$

called differential delays, then the update rules for the parameters of the system are given by [15]

$$\Delta w_i \propto (1 - 2y_i)x_i + 1/w_i, \quad i = 1, 2$$

$$\Delta w_{0i} \propto (1 - 2y_i)$$

$$\Delta w_{ij} \propto (1 - 2y_i)(1 - 2y_j)u_j(t - b_j)$$

$$\Delta b_j \propto -(1 - 2y_i)w_{ij}u_j(t - b_j), \quad i, j = 1, 2, \quad j \neq i$$

$$\dot{u}(t) = u(t) - u(t - 1) \quad (7)$$

### 4. Near Real-Time Separation of Delayed Sources

The BDSS algorithm gives the best results when we average gradients over a number of samples, called a
frame, of the source mixtures and then update the cross delays and weights. Once one epoch (a set of frames) has been processed, the already processed frames of data points are traversed all over again until satisfactory convergence has been achieved. Here, the frame size is small, and an epoch consists of many frames. An epoch is processed repeatedly until all the parameters in (7) change very little from one iteration to the next iteration. This method, although it gives good convergence, causes substantial delay in the processing of new incoming data, which is not desirable in biomedical applications requiring near real-time separation of mixed data. An intuitive approach to obtain convergence in near real-time is achieved by segmenting the incoming mixed data into longer length frames and then repeatedly processing a frame until the parameters in (7) change very little. After several frames have been processed this way, the parameters converge to values that separate the mixtures. A procedure utilizing this approach is described below

1) Collect a fixed number (N) of incoming mixture samples in a single frame, and call it F.
2) Calculate the updates to be made to the delays and weights by iterating over the frame once. This is equivalent to accumulating N gradients and updating the delays and weights.
3) Repeat step 2 until one of the following happens: (a) the upper limit of a number of iterations (sweeps) over a frame is reached, or (b) the updates to delays and weights have become very small.
4) Jump to the next frame F_{i+1}, which consists of new incoming data, and discard frame F_i. However, we have found that by overlapping successive frames, convergence is smoother.
5) Repeat steps 1 to 4 until the delays and weights have converged to constants.

The performance of this algorithm in separating FPCGs will be demonstrated in the next section.

5. Experiments and Results

In real life situations the FPCGs of multiple fetuses do not mix instantaneously at the transducers. There are propagation delays from the sources to the transducers. All BSS algorithms that assume instantaneous mixing will fail to separate the individual FPCGs. Fig. 2 depicts a situation where there can be propagation delays while recording FPCGs from twin fetuses. Considering the recording environment shown in fig. 2, the mixing model is given by

\[ x_1(n) = a_{11} FPCG_1(n - d_{11}) + a_{12} FPCG_2(n - d_{12}) \]
\[ x_2(n) = a_{21} FPCG_1(n - d_{21}) + a_{22} FPCG_2(n - d_{22}) \]

where \( n \) is the sample time index, \( a_{11}, a_{12}, a_{21}, \) and \( a_{22} \) are attenuation coefficients and \( d_{11}, d_{12}, d_{21}, \) and \( d_{22} \) are propagation delays along the corresponding paths. FPCG1 is the phonocardiogram of fetus 1 and FPCG2 is the phonocardiogram of fetus 2. When the network in fig. 1 converges, the estimates of differential delays converge to the true differences \( d_{21} - d_{11} \) and \( d_{12} - d_{22} \), respectively, and the estimates of the cross weights converge to the negative of cross coupling values. We used the mixing model to simulate real life multi-fetal PCG mixing given by

\[ x_1(n) = 0.7s_1(n - 1) + 0.2s_2(n - 6) \]
\[ x_2(n) = 0.3s_1(n - 5) + 0.9s_2(n - 3) \]

An apparatus, similar to a stethoscope, shown in fig. 3 can be used to facilitate multi fetal FPCG acquisition and processing. The multiple sensors in fig. 3 ensure that we have as many recordings as the number of fetuses in the womb. In the absence of real data, the delay and mixing of FPCGs, \( s_1 \) and \( s_2 \), was simulated. The sampling frequency of the FPCGs is 24 KHz. The FPCGs used in the experiments are shown in fig. 4. Here we see 1.8 seconds of each FPCG. The values of the propagation delays in (9) were arbitrarily selected. Assuming that the velocity of sound in human tissue is 1500m/s, the source \( s_1 \) in \( x_2 \) of (9) is delayed by 0.2 milliseconds. Actual values of the propagation delays will depend upon the velocity of sound in human tissue, the distance of each fetus’s heart from the sensor on the mother’s abdomen and the sampling frequency of the A/D converter. For the current mixing simulation, the differential delays are \( b_1 = 4 \) and \( b_2 = 3 \) sampling increments. The initial guesses for \( b_1 \) and \( b_2 \) were set to 1 sampling increments each.

When the delayed source mixtures, shown in fig. 5, were processed by the Infomax algorithm, the separation results shown in fig. 6 were obtained. Notice the extensive cross-talk. The Infomax algorithm (and any BSS algorithm that assumes instantaneous mixing) fails to extract the two FPCGs from mixtures of delayed FPCGs. Instead, we applied the network shown in fig. 1 to separate the delayed source mixtures. Fig. 7 shows the convergence of the weights and differential delays of the separating network. Each iteration on the horizontal axis represents the average of \( N = 200 \) sample gradients, called a frame, to update delays and weights. At first we observe how the differential delays and the cross weights change from their initial values, and then, after 30 seconds
of data has been processed, we see how they converge to the correct values. In fig. 8 the FPCGs are properly separated.

A more practical algorithm to make the delays and weights converge in near real-time is given in Section 5. The results of near real-time operation of the BDSS algorithm are shown in fig. 9 and fig. 10. The frame size was set to $N = 2048$ points with 50% overlap between adjacent frames. For near real-time operation, each epoch was traversed only once. In fig. 9 we see that the weights and delays converge much faster than in fig. 7. Although the convergence of delays and weights is less robust as compared to the BDSS algorithm of Section 3, within a few heart beats the separated FPCGs in fig. 10 are clean enough to be of diagnostic value.

6. Conclusions

We have demonstrated how a multi fetal PCG recording involving propagation delays can be modeled. All known BSS algorithms that assume instantaneous mixing fail to separate mixtures of delayed FPCGs. For multiple fetal pregnancies, the apparatus described here can be used to monitor the FPCGs of each fetus for a long duration non-invasively. The algorithm presented in this paper is capable of separating the FPCGs of any number of fetuses from their mixtures.

7. References


Figure 1. Proposed architecture to separate mixtures of delayed sources.

Figure 2. A typical FPCG recording situation in multi fetal pregnancy.

Figure 3. A stethoscope like instrument that can record FPCGs in a multi fetal pregnancy.

Figure 4. The two FPCGs used in the experimentation.

Figure 5. Delayed mixtures of FPCGs generated with the model in Eq. (10).

Figure 6. Incorrect separation of FPCGs using Bell and Sejnowski’s Infomax algorithm.
Figure 7. Convergence of differential delays (top) and cross weights (bottom) to the separating solution.

Figure 8. Separated FPCGs using the BDSS algorithm of Section III.

Figure 9. Convergence of differential delays (top) and cross-weights (bottom) for near real-time implementation of the BDSS algorithm.

Figure 10. Separation of FPCGs using the near real-time implementation of the BDSS algorithm.