FETAL MAGNETOCARDIOGRAPHIC SOURCE SEPARATION USING THE POLES OF THE AUTOCORRELATION FUNCTION

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ABSTRACT

Fetal magnetocardiography (FMCG) have been extensively reported in the literature as a non-invasive, prenatal technique, in which magnetic fields are used to monitor the function of the fetal heart rate. On the other hand, FMCG may be highly noisy, due to the fetal heart dimensions when compared, for example, to the mother's. In the field of source separation, many works have shown its efficiency of extracting signals even in this condition of low signal-to-noise ration. In this work, we propose an extension of the work of Barros and Cichocki, where they idealized an algorithm to extract a desired source with resonance at a given delay. We model the system as an autoregressive one, and our proposal is based on the calculation of the poles of the autocorrelation function. We show that the method is efficient and much less computationally expensive than the ones proposed in the literature.

1. INTRODUCTION

Traditional techniques to analyze fetal cardiac function and morphology such as cardiotocography and sonographic methodology does not give a clear picture about the fetal heart conductivity, providing an incomplete information about the cardiac system. Therefore, fetal electrocardiography and (FECG) and, more recently, fetal magnetocardiography (FMCG) have been extensively reported in the literature as a non-invasive, prenatal technique [10], in which magnetic fields are used to monitor the function of the fetal heart [11].

The first recording of adult MCG was performed in 1963 and the first fetal QRS complex was first successfully observed in 1974 [6]. The FMCG can be detected as early as 16 weeks gestation, which is much earlier than the FECG can be detected. It is also common to observe smaller waveform components, such as the P-wave, that have allowed us to detect and analyze fetal rhythm disturbances that could not be diagnosed by any other means [12]. Furthermore, an insulating effect influences on the FECG signal by the *Vernix caseosa*. In contrast, FMCG allows the registration of fetal cardiac signals through almost the entire pregancy.

Heart rate have been extensively studied in adult humans and in experimental animals. On the other hand, fetal heart rate (FHR) monitoring is considerably less studied in spite of its important clinical applications. FHR can be used for assessing fetal health and is one of the few specific techniques used to evaluate effects of fetuses heart conduction patterns, providing early and sensitive indicators of growth retardation, hypoxia, and congenital defects. More recently it has been succefully used to investigate different aspects of fetal arrhythmias, such as the congenital heart block [15]. Besides, the fluctuations of the heart beating or *heart rate variability* (HRV) is a useful tool for assessing non-invasively the status of the autonomic nervous system (ANS). A special interest is shown by the scientific community in the analysis of fetal HRV, with the aim of understanding the intra-uterin ANS, or detecting eventual cardiac malfunctions. HRV is usually calculated from an ECG or MCG, after detecting the regular peak that appears in the ECG waveform due to heart beating, called R-wave. However, it could be particularly hard to estimate fetal HRV as, besides other types of noise, it appear corrupted by strong cardiac artifacts from the maternal heart signal.

Recently, using powerful tools of statistical signal processing, a great development was reached through the concept of *blind source separation* (BSS) and *independent component analysis* (ICA). These concepts were successfully used for separating mutually independent signals in a number of areas, including biomedical signal processing [3, 8]. BSS is based on the following principle. Assuming that the original (or source) signals have been linearly mixed, and that these mixed sensor signals are available, BSS finds in a *blind* manner a linear combination of the mixed signals which recovers the original source signals, possibly re-scaled and randomly arranged in the outputs.

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However, extracting all the source signals from the sensors may not be of interest to the user. Rather, one can use some a priori information available about the signal in order to find an important signal. Thus, Barros and Cichocki [2] proposed a quite simple algorithm based on second order statistics which was shown in theory and experimentally that could extract a given signal using its temporal information, given that we knew *a priori* a certain delay where that particular signal would have a resonance.

In spite of that, their algorithm did not show an appropriate method which could calculate that lag. Here we propose to use the poles of the autocorrelation function to find that delay, by modelling the system as an autoregressive one. An advantage of this model is that it is less computationally intensive.

2. METHODS

2.1. Biomagnetic Measurements

The FMCG data was collected in two non-symptomatic fetuses at gestational ages 29 and 32 weeks, where the maternal MCG signal was prominent. The recordings were performed with a 37-Channel biomagnetometer (Magnes II, 4D Neuroimaging) housed within a high-magnetic permeability room. The signals were digitized at 520.8 Hz and were bandpass filtered from 1-80 Hz.

2.2. Source Separation

Let us briefly describe the algorithm of Barros and Cichocki [2] Consider n signals $\mathbf{s} = [s_1, s_2, .., s_n]^T$ which were mixed into a vector $\mathbf{x}$ through the following linear combination,

$$\mathbf{x} = \mathbf{A}\mathbf{s}, \tag{1}$$

where $\mathbf{A}$ is an $n \times n$ invertible matrix. Our purpose here is to find a linear combination of the elements of $\mathbf{x}$ which yields at the output a *desired* source $\mathbf{s}_i$.

As we want to extract only a desired source signal, we can use a single signal described as $y(k) = \mathbf{w}^T\mathbf{x}(k)$, where $\mathbf{w}$ is the weight vector. Then, let us define the following error[1],

$$\varepsilon(k) = y(k) - y(k-p), \tag{2}$$

by minimizing the mean squared error $\xi(\mathbf{w}) = E[\varepsilon^2]$, and making $y(k) = y_p$, we find,

$$\xi(\mathbf{w}) = \mathbf{w}^T E[\mathbf{x}\mathbf{x}^T]\mathbf{w} - 2E[y_p\mathbf{w}^T\mathbf{x}] + E[\mathbf{y}_p^2]. \tag{3}$$

[1]In the original manuscript [2], there was a scalar multiplying the delayed signal, but which was shown to be not necessary, thus, we will ignore it in this work.

Thus, the minimum will be reached by the following condition,

$$\frac{\partial\xi(\mathbf{w})}{\partial\mathbf{w}} = 2E[\mathbf{x}\mathbf{x}^T]\mathbf{w} - 2E[y_p\mathbf{x}] + 2E[\mathbf{x}_p\mathbf{x}_p]\mathbf{w} = \mathbf{0}, \tag{4}$$

$$\tag{5}$$

yielding the following updating rule,

$$\mathbf{w} = \frac{1}{2}E[\mathbf{x}\mathbf{x}^T]^{-1}E[y_p\mathbf{x}], \tag{6}$$

Without loss of generality, we can assume that the data were prewhitened, yielding $E[\mathbf{x}\mathbf{x}^T] = \mathbf{I}$. Thus, performing normalization of the vector to unit length at each iteration step as $\mathbf{w}_* = \mathbf{w}//||\mathbf{w}||$, (6) leads to the following learning rule,

$$\mathbf{w} = E[\mathbf{x}y_p]. \tag{7}$$

2.3. Multivariate AR Modelling

A multivariate matrix $\mathbf{x}(n) = [x_1(n)\cdots x_N(n)]$, where each vector x_i is a stationary time series, may be AR modelled by

$$\mathbf{x}(n) = \sum_{m=1}^{M}\mathbf{\Theta}(m)\mathbf{x}(n-m) + \varepsilon(n). \tag{8}$$

where $\mathbf{\Theta}(m)$, $\mathbf{x}(n)$ and ε are given by

$$\mathbf{\Theta}(m) = \begin{pmatrix} a_{11}(m) & a_{12}(m) \\ a_{21}(m) & a_{22}(m) \end{pmatrix}, \tag{9}$$

$$\mathbf{x}(n) = \begin{pmatrix} F0(n) \\ BP(n) \end{pmatrix}, \tag{10}$$

and $\varepsilon(n) = \begin{pmatrix} \epsilon_1(n) \\ \epsilon_2(n) \end{pmatrix}$.

M is the model order and ε is a vector of independent random variables with zero mean and Gaussian distribution. We define the autocorrelation matrix of ε as $\Sigma = E[\varepsilon\varepsilon^*]$, where $*$ is the conjugate transpose.

To analyze matrix $\mathbf{x}$ in the frequency domain, we should estimate the autoregressive coefficients of matrices $\mathbf{\Theta}$ and Σ. The cross power spectra $\mathbf{P}(f)$ of $\mathbf{x}$ for this case is given by

$$\mathbf{P}(f) = \mathbf{F}(f)\Sigma\mathbf{F}(f) \quad (0 \le f \le 0.5), \tag{11}$$

where $\mathbf{F}(f)$ is the frequency response given by

$$\mathbf{F}(f) = [\mathbf{I} - \sum_{m=1}^{M}\mathbf{\Theta}(m)e^{-i2\pi fm}]^{-1}, \tag{12}$$

with $\mathbf{I}$ being the identity matrix.

The idea here is to estimate the coefficients of matrix $\mathbf{\Theta}$ and from them, calculate the poles of a transfer function which models the whole system in the following way,

$$H(z) = \frac{1}{1 - \sum_{j=1}^{M} \Theta(m) z^{-j}} \tag{13}$$

In this work, the coefficients of matrix $\mathbf{\Theta}$ were calculated by the Yule-Walker method, as in [7]. The model order was selected using the Akaike information criterion (AIC). AIC is a criterion of statistical estimation that selects the order that best fits a given time-series.

3. RESULTS

Figure 3 shows the signal from 10 seconds of data where one can see that the maternal MCG and the fetal MCG are overlapping in time.

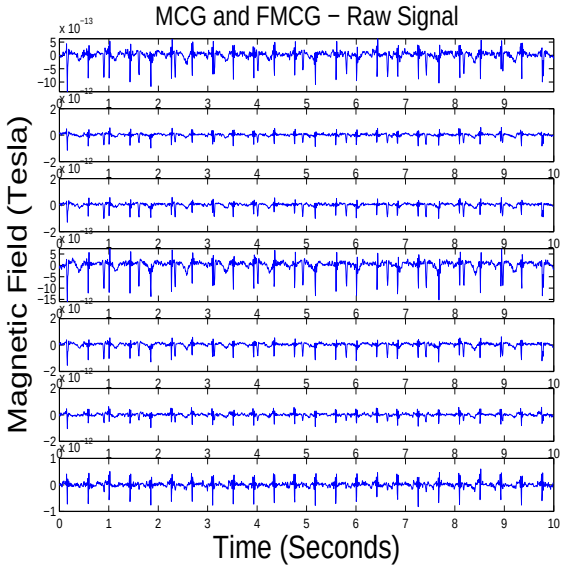

Figure 1: Ten seconds of raw data, from five of the 37 biomagnetic channels, of the fetal MCG contaminated by the signal from the maternal heart.

We applied the proposed algorithm to extract the FMCG from an actual recording. We shown in Figure 3 a power spectrum of a single recording. After finding the autoregressive coefficients by the Yule-Walker method, we calculate the roots which corresponded to their poles. Then, we found the nearest integer number corresponding the inverse of that resonant frequency and applied the Barros and Cichocki algorithm.

Applying the algorithm after finding poles at 1.5 Hz, which is more consistent with an adult heart beating and 2.4 Hz, consistent with a fetal heart beating,

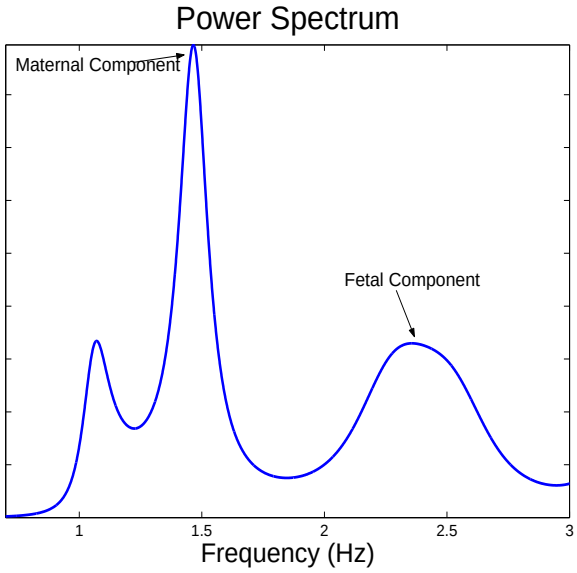

Figure 2: Power spectrum of one single recording. One can see two peaks corresponding to the fetal and maternal components.

the method revealed two components. The results are shown in figure 3. One can see that the fMCG is clearly preserved, excluding the maternal interference.

4. DISCUSSION

Magnetocardiogram has been shown to be a promising technique for measuring the fetal cardiac activity. This is due to its high sensitivity to magnetic fields in different parts of the human body. However, this characteristic affects negatively the measurements as more noise come out together with the desired signal. Thus, techniques are necessary to remove those artifacts. In fetal MCG signals the main source of interference is the maternal MCG.

Different methods for removing the maternal interference have been developed for fetal electrocardiography. Most of them are based on choosing an interference template, say the maternal ECG, which is removed as long as the interference is detected. These matched filtering algorithms are efficient whenever the morphology of the signal does not change. However, this is not the case in MCG recordings, since artifacts such as the maternal breathing always affect the topography of the signal. Another problem in these methods arises when the maternal and fetal signals overlap. In a typical fMCG study this overlapping occur very frequently.

One interesting approach was proposed by Chen *et al.*[4], and recently updated by Wakai and Lutter [13]

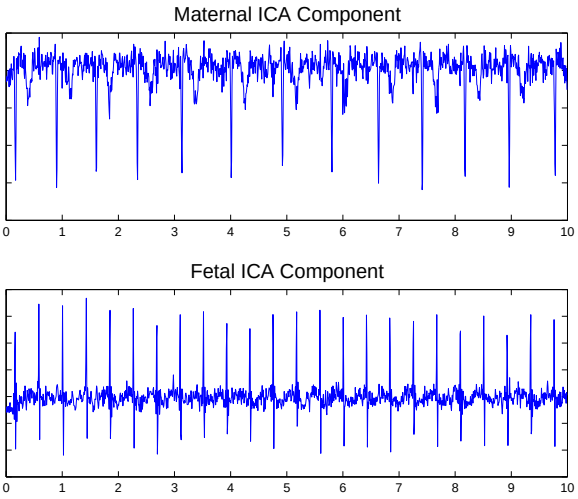

Figure 3: Separated components of the fetal MCG and Maternal MCG.

which a spatial filtering algorithm based on eigenvector constraints that extracts the fetal information from the signal even if there is an overlap between maternal and fetal data. However, that method may be time consuming, as long as one has to find a template to match the maternal MCG.

We propose here to rather use the assumption of mutual independence of the signals composing the measured MCG. This is not at all a strong assumption as, to our knowledge, there is no evidence showing any correlation between fetal and maternal heart beating.

The advantage of the approach proposed here is that, given a *rough estimation* of the fetal heart rate, the method can immediately find the corresponding component to that frequency. Indeed, this is carried out by find the pole which is closer to that estimation. This fact turns the fMCG analysis method more user friendly than the template matching. Another advantage is that of the autoregressive modelling. Usually, the number of poles is not larger than five, which turns the computational load quite small.

5. REFERENCES

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