FETAL HEART RATE VARIABILITY EXTRACTION BY FREQUENCY TRACKING

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ABSTRACT

In this work, we propose an algorithm to extract the fetal heart rate variability from an ECG measured from the mother abdomen. The algorithm consists of two methods: a separation algorithm based on second-order statistics that extracts the desired signal in *one shot* through the data, and a hearth instantaneous frequency (HIF) estimator. The HIF algorithm is used to extract the mother heart rate which serves as reference to extract the fetal heart rate. We carried out simulations where the signals overlap in frequency and time, and showed that the it worked efficiently.

Keywords: Source separation, Independent component analysis, Analytic Signal, A priori information, Second order statistics, Auto-correlation.

1. INTRODUCTION

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). And 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 electrocardiogram (ECG), after detecting the regular peak that appears in the ECG waveform due to heart beating, called R-wave (see Fig. 1), and computing the time difference between two consecutive R-waves. The HRV signal is the sequence of these differences. However, this method has the disadvantage of needing more memory for storage and being more sensitive to noise, specially in the case of fetal HRV, as the fetal ECG (FECG) appear corrupted by strong cardiac artifacts from the mother, as shown in Fig. 1.

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 [24, 18, 22, 4]. 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,

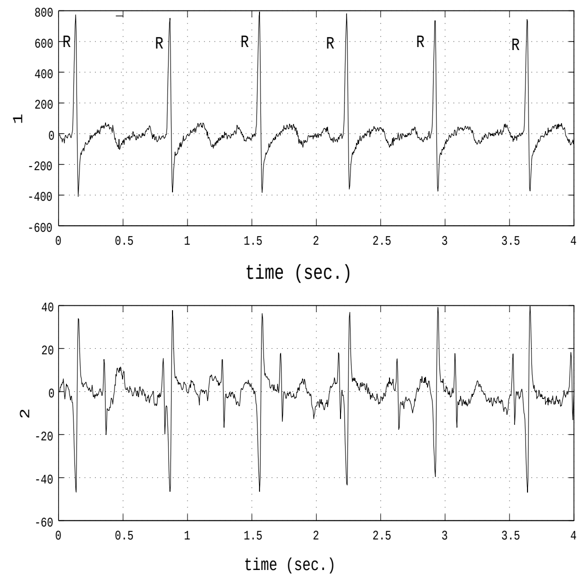

Fig. 1. Example of an ECG signal from a pregnant woman. (1) No fetal influence appears (stronger and slower). (2) The fetal influence can be noticed (weaker and faster).

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.

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 temporal information. On the other hand, Barros and Ohnishi[3] proposed a new method called *heart instantaneous frequency* (HIF) which showed to be an efficient estimator of HRV using the spectral response of the cardiac signal.

Here we propose an algorithm which extracts the fetal heart rate by combining the above concepts of blind source separation and heart instantaneous frequency. Our method is designed by using, instead of real signals, the *analytic signal* along with the exponential notation. The idea is to use the HIF calculated from the mother ECG to extract the fetal heart rate. Another contribution of this work is that there is no need to have various sensor measurements, as usually needed by the BSS community, because we use only part of the spectral response of the sensors, diminishing therefore the possibility of various sources contributing at the same time to the mixing process. An advantage of the present approach over the one of Barros and Cichocki [2] is that we now assume that the signal to be extracted can be non-stationary and have a time-varying frequency.

Thus, we divide this manuscript in the following form. Firstly, we present the method, composed by HIF and the proposed BSS algorithm. In particular, this algorithm uses the time-varying mother heart instantaneous frequency to extract the fetal contribution to the ECG. Then, we show simulations and some experimental results. In the next section, we discuss the results and carry out the conclusions.

2. METHODS

We model here the ECG as a quasi-periodic signal with a fundamental plus infinite harmonic frequencies as shown below,

$$x(t) = \sum_{i=-\infty}^{\infty} c_i(t) e^{j i \pi \omega_0(t)}, \quad (1)$$

where $\omega_0(t)$ is the fundamental frequency and $c_i(t)$ is a time-varying amplitude modulator.

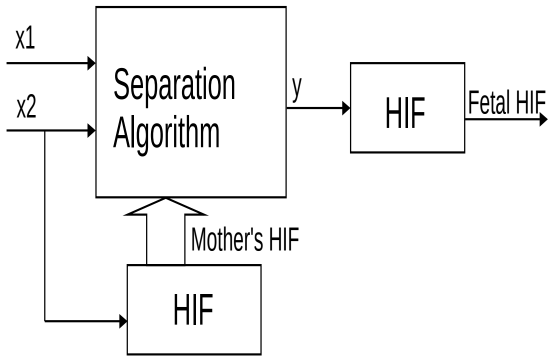

Fig. 2. Block diagram of the proposed method, composed of a *separation algorithm* and *heart instantaneous frequency* (HIF)extractor. From two ECG measurements x_1 and x_2, where the fetal and maternal signals are mixed, and by using the mother's HIF, the separation algorithm extracts the fetal contribution y, from which the fetal HIF is calculated and output.

Figure 2 shows the block diagram of the proposed algorithm. Essentially, it is grounded on two methods: HIF and a separation algorithm. Firstly, from one of the ECG sensors, we calculate the mother's HIF, which serves as reference to the separation algorithm to extract the fetal ECG $y(k)$ and from this, extract the fetal ECG.

2.1. Heart Instantaneous Frequency

For a given signal $x(t)$, the corresponding analytic signal $\upsilon(t)$ is given by,

$$\upsilon(t) = x(t) + jH[x(t)], \; H[x(t)] = \frac{1}{\pi}\int \frac{x(\tau)}{t-\tau} d\tau, \quad (2)$$

where $H[x(t)]$ is the Hilbert transform of $x(t)$. An advantage of the analytic signal is that it can define uniquely a modulation, dealing with exponentials.

As carried out in the signal processing literature (e.g. [7]), frequency modulation lead us to the possibility of using the concept of the *instantaneous frequency*. For signal $x(t)$, the instantaneous angular frequency $\omega_0(t)$ is calculated from the analytic signal and is given by

$$\omega_0(t) = \frac{d\phi_0(t)}{dt}, \qquad \phi_0(t) = \arctan\left(\frac{-H[x(t)]}{x(t)}\right). \quad (3)$$

We call the heart rate variability estimated from the ECG spectral response as the *heart instantaneous frequency* (HIF), which involves first the estimation of the spectrogram. The spectrogram for a given signal $z(t)$ is defined as

$$P(t,f) = \left|\frac{1}{2\pi}\int e^{-j2\pi f t} z(t) h(t-\tau)\right|^2. \quad (4)$$

We then look for the frequency value corresponding to the maximum of $P(t,f)$ at each time instant in a given frequency range. We call this quantity the *driver* $\delta(t)$, and it is given by

$$\delta(t) = f : \max\left[P(t,f)\right]_{\delta(t-1)-\alpha}^{\delta(t-1)+\alpha}. \quad (5)$$

After this, we calculate the instantaneous frequency by using a band-pass filter around a central frequency given at each time instant by the *driver*. In particular, we use wavelets to construct the filter. The basic wavelet is

$$\Psi(t) = \frac{1}{2\pi}\frac{d}{dt}\left[e^{-\pi\left\{\frac{\overline{\delta(t)}t}{2}\right\}^2} \cos\left(2\pi t \int_\Omega \delta(t) dt\right)\right],$$
$$\overline{\delta(t)} = \frac{1}{\Omega}\sum_\Omega \delta(t). \quad (6)$$

where Ω is a short time interval. The filtered signal is given by

$$x(t) = \int_{-\infty}^{t} \Psi(t) z(t) d\tau. \quad (7)$$

The heart instantaneous frequency $\omega_0(t)$is then calculated using (3).

2.2. Proposed BSS Algorithm

Let us make some preliminary definition, by denoting the source signal vector as $\mathbf{s}(k) = [s_1(k) \dots s_n(k)]$ and the mixed vector as $\mathbf{x}(k) = [x_1(k) \dots x_n(k)]$, where the mixture is written as $\mathbf{x}(k) = \mathbf{A}\mathbf{s}(k)$, k is the sampling number, and $\mathbf{A}$ is an $n \times n$ nonsingular matrix.

Because we want to extract only the desired source signal, say $s_i(t)$, we can use a simple processing unit described as $y(k) = \mathbf{w}^T\mathbf{x}(k)$, where $y(k)$ is the output signal and $\mathbf{w}$ is the weight vector. Then, let us first define the following error,

$$\varepsilon(k) = y(k) - e^{-j\phi_0(k)}. \quad (8)$$

The idea is to carry out the minimization of the mean squared error $\xi(\mathbf{w}) = E[\varepsilon^2]$. From (8), and dropping the index k for convenience, we find,

$$\xi(\mathbf{w}) = \mathbf{w}^T E[\mathbf{x}\mathbf{x}^T]\mathbf{w} - 2E[e^{-j\phi_0}\mathbf{w}^T\mathbf{x}] + E[e^{-2j\phi_0}]. \quad (9)$$

This cost function achieves minimum when its gradient reaches zero in relation to $\mathbf{w}$. Thus, taking into account that $y = \mathbf{w}^T\mathbf{x}$, we find,

$$\frac{\partial\xi(\mathbf{w})}{\partial\mathbf{w}} = 2E[\mathbf{x}\mathbf{x}^T]\mathbf{w} - 2E[e^{-j\phi_0}\mathbf{x}] = \mathbf{0}. \quad (10)$$

Now, we can solve this equation by the following algorithm,

$$\mathbf{w} = E[\mathbf{x}\mathbf{x}^T]^{-1}E[e^{-j\phi_0}\mathbf{x}], \quad (11)$$

We can also assume that the sensor vector has been prewhitened so that $E[\mathbf{x}\mathbf{x}^T] = \mathbf{I}$, with this, (11) sleads to the learning rule,

$$\mathbf{w} = E[\mathbf{x}e^{-j\phi_0}]. \quad (12)$$

We propose to use ϕ_0 or ω_0 as in (3). With some more reasoning, one can notice that this algorithm also avoids the so-called permutation/scaling problem which usually happens in ICA theory, by using a priori information on the phase.

3. RESULTS

We carried out simulations to test the validity of the proposed separation algorithm. Here we show one where we mixed two different source signals: one with increasing and another with decreasing frequency with time, while they cross one another in frequency. The signals were $s_1(t) = B(t)sin[2\pi(t/600 + 1)t]$ and $s_2(t) = B(t)sin[2\pi((400 - t)/600 + 2)t]$, where $B(t)$ is a Bartlett window. They were chosen because they overlap temporarily in frequency, as

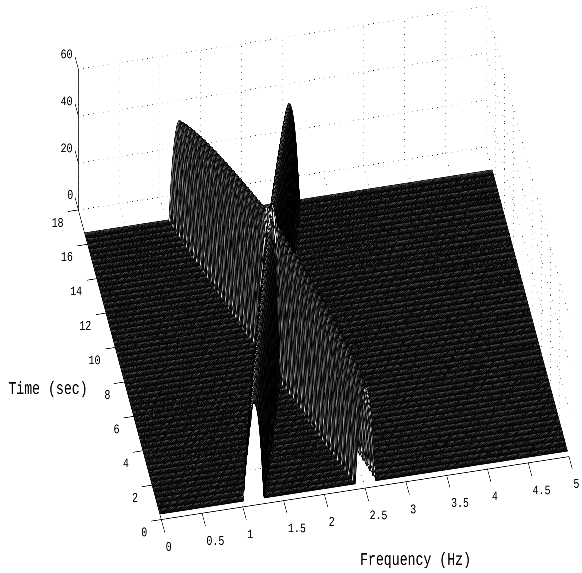

Fig. 3. Spectrogram of the sum of the two source signals. Notice the frequency overlapping. In this case, regular filters shall not work.

shown by the spectrogram of their sum in Fig. 3, and regular algorithms [5, 23] shall not work. It is important to notice that the source signals are amplitude and frequency modulated at the same time. We mixed randomly the source signals to generate sensor signals and used the *a priori* frequency information to extract either signal. In all the cases the proposed separation algorithm worked efficiently.

We tested also our algorithm to the ECG data. We simulated a mixture of two ECGs measured originally from adults and decimated one of them by a factor of two in order to have a simulated fetal ECG. Their spectral response up to 10 Hz are plotted in Fig. 4. It is important to notice that the fundamental frequency of the FECG is around 2 Hz, which overlaps with the first harmonic of the mother ECG. This stands a problem for regular filters on which HIF algorithm is based on. As we can see from Fig. reffig:res, even if the signals are mixed, the mother fundamental frequency remains *clean*. Thus, we used this frequency information to make sure we were extracting the mother ECG signal. As proposed in the block diagram in Fig. 2, we removed this signal from the sensors, from which we estimated the fetal HIF. As we had the original FECG, from its R-waves we found the heart rate variability. We show this HRV and the extracted HIF in Fig. 5.

4. DISCUSSION

As we can see from the results, the proposed algorithm worked efficiently in two difficult cases where the source signals overlapped in time and frequency. Moreover, it is

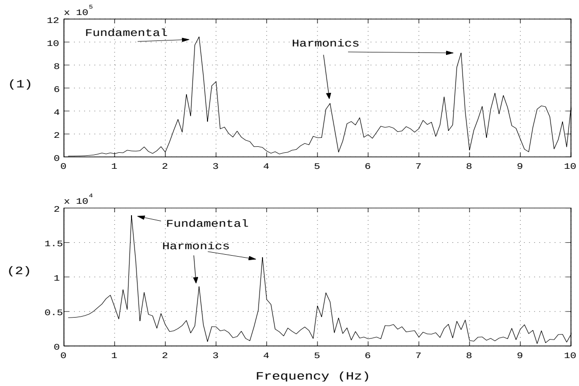

Fig. 4. Spectral response of two source signals simulating a (1) fetal and (2) a maternal ECG measurements. Notice the spectral overlap around 2 Hz.

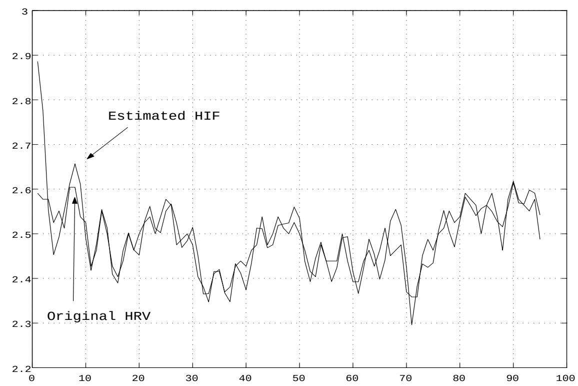

Fig. 5. Comparison between the fetal heart rate variability measured (1) from the ECG R-wave and (2) by the proposed heart instantaneous frequency (HIF) algorithm.

worth to emphasize that this algorithm, contrary to proposed ones, reaches convergence in one shot through the data.

On the other hand, extracting signals from a corrupted environment has been an old issue in statistical signal processing, with different approaches which evolved together with machines computational power. In this context, different statistical tools were used. Firstly, second order statistics (SOS) by the estimation of correlations, and after, higher order statistics (HOS), involving for example the estimation of skewness and kurtosis, were proposed. However, the calculation of HOS moments are more sensitive to data size then SOS. Thus, our algorithm shows also this advantage, since it needs only the calculation of a second order moment.

It is important to emphasize that the energy of the maternal ECG is much stronger than the fetal ECG, besides, the fundamental frequency of the FECG usually overlaps the first harmonic of the MECG. Thus, source separation stands as a strong tool for solving this problem.

We also believe that it can be useful in other applications. For example, in biomedical signal processing especially in EEG/MEG, e.g., for some experiments with event related potentials (ERP), where the timing is controlled. Equally, the proposed algorithm can be used in speech/audio and telecommunication applications.

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