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Procedia Computer Science 134 (2018) 322–327

Procedia Computer Science

www.elsevier.com/locate/procedia

The 2nd International Workshop on Big Data and Networks Technologies (BDNT'2018)

Blind Maternal-Fetal ECG Separation Based on the Time-Scale Image TSI and SVD – ICA Methods

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Abstract

Fetal heart monitoring yields vital information about the fetus health and can support medical decision making in critical situations. A compound signal is obtained noninvasively by placing electrodes on the abdomen area of the mother which contains maternal and fetal ECG signals contaminated by various other signals from body and externally induced noises. As a result, the basic problem is to extract the fECG signal from the mixture of mECG and fECG, where the interfering mECG is a much stronger .This problem has been addressed in several works, in this paper, we propose a novel blind-source separation method to extract fetal ECG when given only a single channel recording .Our approach is based on the wavelet theory and SVD-ICA methods. It is pointed out that the presented algorithm is validated by Matlab simulation and can be implemented on real time life by using embedded system such as DSP processor.

Peer-review under responsibility of the scientific committee of the 13th International Conference on Future Networks and Communications, FNC-2018 and the 15th International Conference on Mobile Systems and Pervasive Computing, MobiSPC 2018.

Keywords: Electrocardiogram ECG; Continuous wavelet transform; SVD; ICA

1. Introduction

Congenital heart defects are among the most common malformations at birth and the leading cause of newborn death. Most cardiac abnormalities are visible in the morphology of cardiac electrical signals, which are recorded by electrocardiography which seems to contain more information compared to conventional sonographic methods.

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1877-0509
Peer-review under responsibility of the scientific committee of the 13th International Conference on Future Networks and Communications, FNC-2018 and the 15th International Conference on Mobile Systems and Pervasive Computing, MobiSPC 2018.
10.1016/j.procs.2018.07.179

Therefore, the non-invasive study of the fetal heart signals can provide an effective means to control the proper functioning of the fetal heart and can be used for the early detection of cardiac abnormalities. Many different methods [1, 2, 3, 4, 5] have been developed for detecting the fetal ECG. Most of these methods focus on multi-channel mixtures of signals. Ziani et al [1] developed a method for single channel signals by Segmentation of the time scale image without recourse to statistical methods [5,6,7,8]. The model that we are going to expose is based on the equivalence between the signal studied and a time-scale representation (TSI) of this signal. To separate the signal into several sources is thus reduced to separate this time-scale image into several independent representations (TSIs) supposed to represent them. The decomposition of the timescale representation is ensured by the singular value decomposition (SVD) of the representative matrix of this image whereas the criterion of independence is ensured by the ICA (analysis in independent components).

2. Theoretical background

2.1. The Time –Scale image :TSI

The continuous wavelet transform CWT of a continuous signal is defined as [9]

$$\mathbf{T\ (a,\ b)} = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \qquad (1)$$

This equation contains both dilated and translated wavelet $\psi(\ t-b/\ a\ )$ and the x(t) signal. The normalized wavelet is often written more compactly as

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right)$$

At a specific scale a and location b the relative contribution of the signal energy is given by the two-dimensional wavelet energy density function:

$$\epsilon(a,b) = |T(a,b)|^2 \qquad (2)$$

A plot of $\epsilon(a,b)$ is known as a ***scalogram*** or ***Times- scales image TSI.***

2.2. Singular-Value Decomposition : SVD

The singular value decomposition, SVD allows separating a matrix into several orthogonal components (in other words decorrelated from the statistical point of view). A real matrix S
of size m × n is broken down as follows:

$$\mathbf{S = U\Sigma V^T} \qquad (3)$$

Where **Σ** is a diagonal matrix of size **m × n** with positive real coefficients (generally ranked in descending order) and **U** and **V** are two real matrices orthogonal of respective sizes m × m and n × n, and where **T** denotes the transposition. If we decompose the time-scale image **S**, the columns u_i of U represents frequency characteristics of S decorrelated two by two and the columns v_i of V represents the temporal characteristics of S also decorrelated two by two [12]. The following equation

$$S = \sum_{i=1}^{\min(n,m)} \sigma_{ii} u_i {v_i}^T \qquad (4)$$

Shows that the time-scale representation is expressed as a sum of representations of type $u_i {v_i}^T$ uncorrelated which we associate an amplitude σ_{ii}. Each frequency characteristic u_i therefore corresponds to a temporal characteristic v_i and to an energy σ_{ii}

2.3. Independent Component Analysis :ICA

Consider n signals s_1 (t),. . . , s_n (t) independent statistically called sources. Recall briefly that it is assumed that each source is formed of observations of random variables independently and identically distributed (i.i.d) and that can therefore be used statistical formalism and the notion of independence. The principle of the ICA is to find these sources from n observations x_1 (t),. . . , x_n (t) of their mixture, assumed linear, instantaneous and invertible. As part of the model that we study, the signals observed are the columns of the matrix U resulting from the SVD.

The model is thus expressed in vector form:

$$\mathbf{x}\ (\mathbf{t}) = \mathbf{As}\ (\mathbf{t}) \qquad (5)$$

A is called a mixing matrix.
The problem therefore comes down to calculating a demixing matrix B such that:

$$\mathbf{y}\ (\mathbf{t}) = \mathbf{B}\ \mathbf{x}\ (\mathbf{t}) \qquad (6)$$

Correctly estimate the sources.

3. Methods

3.1. ECG recordings

Our goal is to extract the fECG signal from single channel which contains maternal and fetal ECG signals (MECG and FECG). The data is extracted from the DaISy database [10] (Database for the Identification of Systems). The sampling frequency is 250 Hz. We used the MATLAB 2015 a on Windows 7. This record is shown in the following figure (Fig 1).

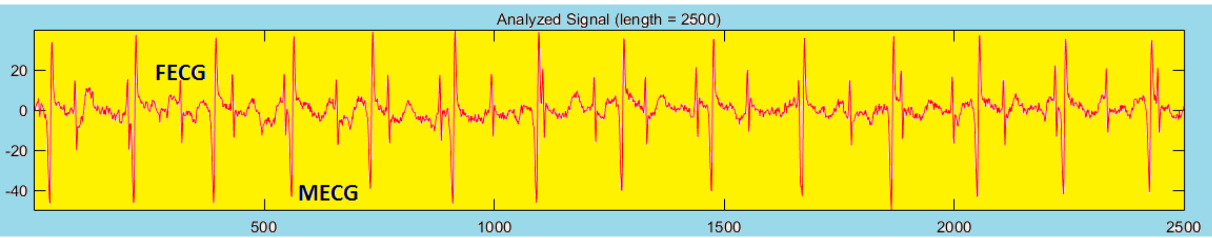

Fig.1. Abdominal signal (fetal and woman)

3.2. Algorithm

We present in this section the global algorithm Fig (2) of our approach, which we will simulate later.

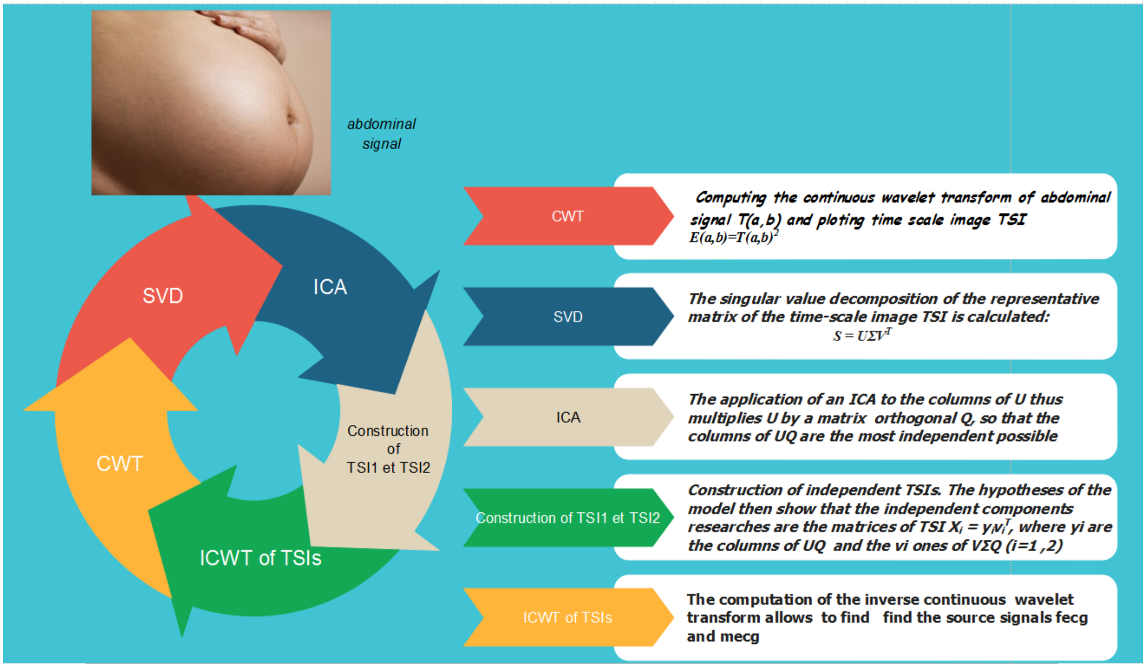

Fig. 2. Algorithm

4. Results

4.1. Time-Scale Image

The results are shown in Fig (3).We used the “sym4” wavelet

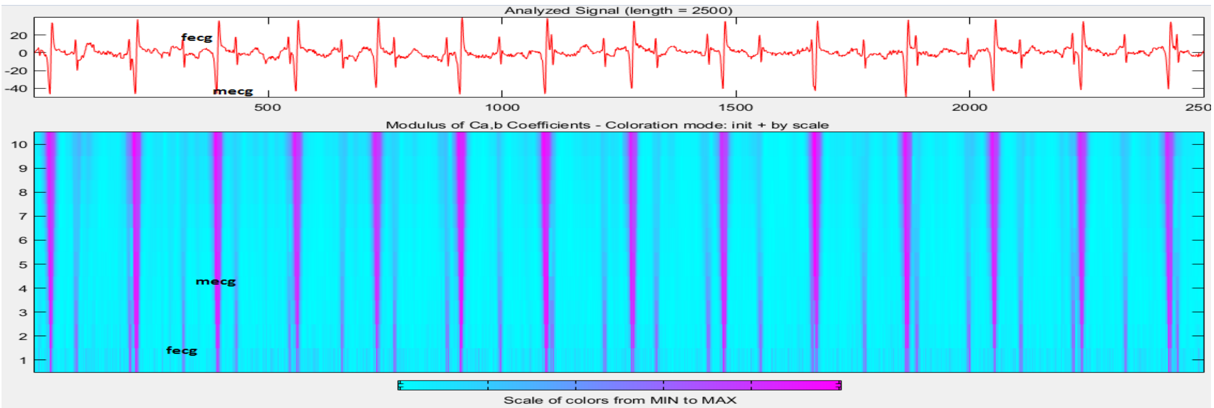

Fig.3. Time-Scale image TS

We see above (fig 3) that the time-scale image contains the contribution of the cardiac activity of the mother and her fetus. The maximum frequency of the spectrum of an ECG signal is 100 Hz that is why we used a sampling frequency of 250Hz

4.2. Extraction of Fecg and Mecg

As indicated in the algorithm see Fig. 2, the application of the SVD to the representative matrix of the TSI image provides:

$$\mathbf{S = U\Sigma V^T}$$

Where $\boldsymbol{\Sigma}$ is a diagonal matrix of size $\mathbf{m \times n}$ with positive real coefficients (generally ranked in descending order) and **U** and **V** are two real matrices orthogonal of respective sizes m × m and n × n, and where **T** denotes the transposition. If we decompose the time-scale image **S**, the columns u_i of U represents frequency characteristics of S decorrelated two by two and the columns v_i of V represents the temporal characteristics of S also decorrelated two by two [12].
The application of ICA to the columns of U thus multiplies U by a matrix orthogonal Q, so that the columns of UQ are the most independent possible. The hypotheses of the model then show that the components independent researchers are the matrices of TSI

$$\mathbf{X_i = y_i v_i^T}$$

Where the y_i are the columns of UQ and the v_i ones of VΣQ.

After SVD and ICA we will reverse the two TSI obtained in order to obtain the time signals fECG and mECG

The results of simulation on Matlab 2015a are shown in the following figures (4 and 5):

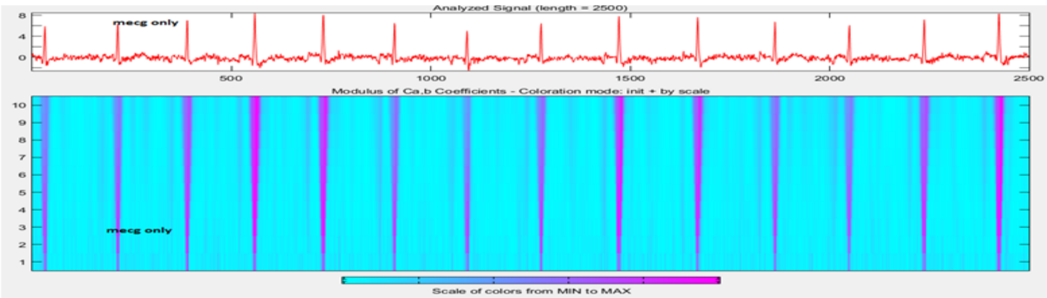

Fig. 4. MECG signal

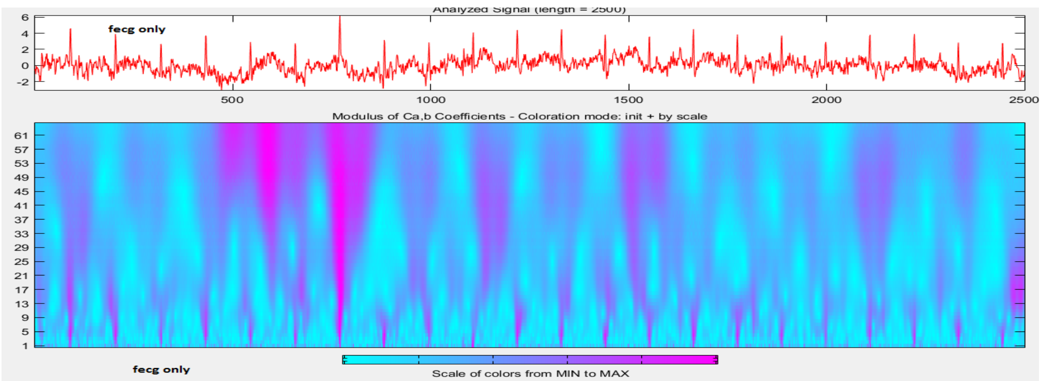

Fig. 5. FECG signal

5. Discussion and Conclusion

The algorithm presented in this paper combines for the first time the continuous wavelet transform and the SVD and ICA methods. Although the separation did not make a complete detection of all the waves contained in an ECG signal but it allows a very good detection of the QRS complex AS AN IMPORTANT INDEX for determining pathologies. Compared to current work [11, 12, 13] and more particularly those using the time-scale image [1] the quality of the separation is less important and this is due to the use of the SVD method which is based on energy values, but we let's look at the signal fECG which is low energy compared to that of the mother and therefore the great difficulty to reconstitute a complete information on the source (heart of the baby). And this constitutes a good opening for future works.

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