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A New Approach Based On Wavelet-ICA Algorithms For Fetal Electrocardiogram Extraction

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Abstract. The fetal electrocardiogram (fECG) monitoring yields important information about the fetus condition during pregnancy and it consists in collecting electrical signals by some sensors on the body of the mother. The Independent Component Analysis (ICA) has been widely exploited to isolate the fECG, while wavelet transform has been used as post-processing tool. Here we propose to fit the recently developed Wavelet-ICA method, based on the joint use of Wavelet Analysis and ICA, to fECG extraction, in order to improve the extraction performance. We also show a comparison with other techniques and we discuss the advantages of the proposed method.

1 Introduction

The fetus heart health can be monitored by invasive and non-invasive techniques, the fetal electrocardiogram (fECG) monitoring is developing to become a tool for prenatal diagnosis. It consists in collecting electrical signals generated by the fetal heart by some sensors on the body of the mother. Despite its limitations, the fetal heart rate (FHR) tracing analysis is the best monitor of the fetal wellbeing during labour and fECG shape monitoring can show cardiac pathologies.
Unfortunately, the fetal heartbeat signal yielded by this recording technique is quite weaker than the mother heartbeat signal, also due to the attenuation during the propagation caused by the tissues; moreover, many other signals are superimposed to the two heartbeats: artifacts such as motherbreathing, uterine contractions, diaphragm, electrical line noise. Because of the low amplitude and the poor SNR, the fECG is hopelessly contaminated by the artifacts, therefore it is quite difficult to extract its shape, it is desirable to extract it and to trust a R-wave (see the Figure 1) extraction procedure as steady as possible towards the artifacts.

The fECG extraction is a typical blind source separation (BSS) problem and the first application of BSS techniques to fECG extraction was done by De Lathauwer et al. [1], it is well accepted that Independent Component Analysis (ICA) is a suitable tool for separating the fECG "source" from the rest; some different ICA based procedures has been exploited so far: ICA estimated by INFOMAX algorithm [2] (applied to a dataset with eight sensors), ICA by JADE algorithm and a Wavelet-postprocessing consisting in baseline removal and denoising [3] (applied to five sensors), Singular Value Decomposition (SVD) and ICA by FastICA algorithm [4] (applied to a single channel recording), ICA by MERMAID algorithm [5] (applied to eight channels), a sensor array and electrode selection algorithm for fECG extraction by ICA proposed by F. Vrins et al. [6] (applied to one hundred sensors).
Here we propose the adaptation of the recently developed Wavelet-Independent Component Analysis (WICA) method [7, 8] to the fECG extraction problem, in order to improve the reliability of the FHR extraction and to extract the fECG shape.
The paper is organized as follows: Section 2 describes the adaptation of WICA method to fECG extraction, Section 3 reports a comparison with other techniques and the results.

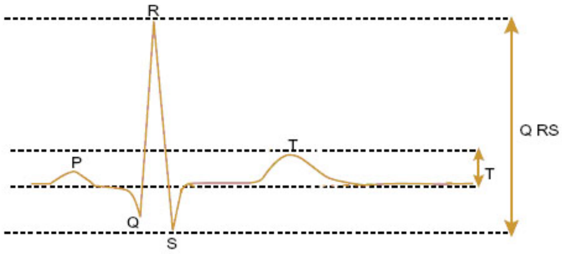

Figure 1: The fECG shape.

.2 WICA approach for fECG extraction

The WICA method was proposed for the first time for an application on electromyographic signals [7,8]. This method merges the advantages of wavelet decomposition and independent component analysis, wavelets are not only used as a denoising or filtering tool, but the wavelet decomposition projects each raw data into a n-dimensional orthogonal basis (consisting of the scaling function and the wavelet functions) where n-1 is the number of levels of the decomposition, while the redundancy is increased and the ICA performance is improved, therefore the decomposition is an integral part in the separation process.
The wavelet expansion of a signal $x(t)$ has the following expression:

$$x(t)=\sum_k c_{j_o k}\varphi_{j_o k}(t)+\sum_{j=j_0}\sum_k d_{jk}\psi_{jk}(t)$$

There are two terms: the first one is the “approximation” and the second one represents the “details”, d_{jk} are the details coefficients and are defined by the equation:

$$d_{jk} = \int x(t)\psi^*_{jk}(t)dt$$

And ψ_{jk} are called wavelet functions:

$$\psi_{jk}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k2^j}{2^j}\right)$$

The approximation coefficients are:

$$c_{jk} = \int x(t)\varphi^*_{jk}(t)dt$$

And φ_{jk} are called scaling functions:

$$\varphi_{jk}(t) = \frac{1}{\sqrt{2^j}}\varphi\left(\frac{t-k2^j}{2^j}\right)$$

In Figure 2 the WICA method fitted to fECG extraction is depicted: the first stage is a discrete wavelet decomposition, the number of levels was set at 6 and the wavelet decomposition-reconstruction were performed by biorthogonal wavelets [9], because the wavelet functions belonging to this family have a shape which is close to the ECG shape. Once the raw data have been so projected into the *n*-dimensional space, the wavelet components (approximations and details) related to fECG are selected by visual inspection and a new dataset **x** is built with them.

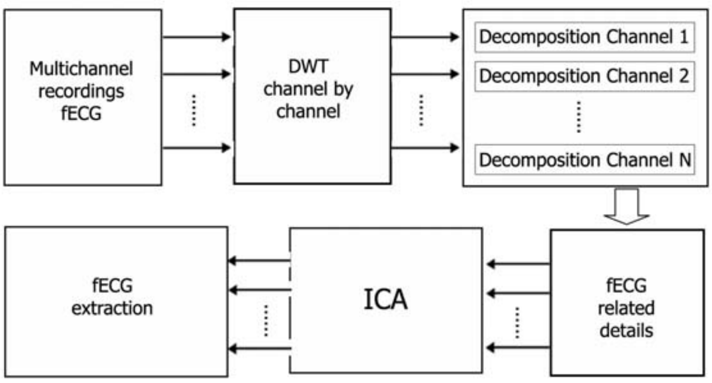

Figure 2: The WICA method for fECG extraction.

The new dataset was processed by ICA, in particular by the extended-INFOMAX algorithm [10] and the independent components (ICs) have the following expression:

$$\mathbf{y} = \mathbf{W}\mathbf{x}$$

where **W** is the demixing matrix computed according the extended-INFOMAX learning rule [10]; once the ICs are extracted, the IC accounting for fECG is selected. In the next section we summarize the results yielded by WICA method and we also show a comparison with another method which proved to be efficacious and which is based on ICA, wavelet baseline removal and wavelet denoising [3].

3 Results

The data consist in multichannel ECG recordings collected simultaneously by 8 sensors placed on the mother abdomen (channels 1-5) and thorax (channels 6-8), the data were sampled for 12.5 seconds at 200Hz, these data are from the Database for the Identification of Systems [11]. The recordings are shown in Figure 3, the maternal ECG (mECG) is clearly visible, whereas the fECG is barely visible because it is completely overcome by mECG and artifacts, as mother breathing and noise.

In order to test the WICA performance and to compare it with another efficacious technique proposed in [3], we have at first applied this technique: the data were processed by ICA and the component accounting for the fECG was selected by visual inspection, the baseline was removed rejecting the approximation in a discrete six level biorthogonal wavelet decomposition, then the signal was denoised by wavelets. The wavelet denoising procedure involves a wavelet decomposition step, depending on the chosen wavelet function and number of levels, a thresholding rule application step and a reconstruction step. We applied the same biorthogonal six levels decomposition, and the details were processed by soft Stein's unbiased risk estimate (SURE) thresholding rule, the denoised signal is reconstructed by the approximation and the processed details. The resulting signal is depicted in Figure 4.a, the FHR can be determined but there are noncardiac spikes which could compromise the monitoring, moreover the Q and S waves are not emphasized.

The second stage of our work was to test the WICA method for fECG extraction, which was described in Section 2. At first we passed the data through the discrete six level biorthogonal wavelet decomposition, then we looked for the fECG related wavelet components by visual inspection, for each channel: we could identify the breathing artifact in the approximations ([0-1.56]Hz) and in the last level details ([1.56-3.12]Hz), in fact, the breathing artifact is a typical low-frequency wave and it unfortunately overcomes other low frequency waves such as P and T fetal ECG waves (see the Figure 1), therefore the approximations and the last level details were not selected for the new dataset. The first level details ([50-100]Hz) accounted for noise and they were not selected for the new dataset too. We detected fetal spikes in the second ([25-50]Hz), third ([12.5-25]Hz) and fourth level ([6.25-12.5]Hz) wavelet components, so they were selected, for each channel, to build the new dataset. Once the dataset was built, it was processed by ICA, as described in Section 2. The ICA processing yielded the ICs and the component accounting for the fetal beat was selected and it is plotted in Figure 4.b. The signal extracted by WICA, is a quite clean and regular signal accounting for fetal heart rate and the effect of the artifacts related spikes is suppressed, furthermore, the Q, R and S waves are visible and it is worth to point out that the signal plotted in Figure 4.b was obtained without any PQRST amplification, while the signal in Figure 4.a needs an additional PQRST amplification processing, according to the procedure described in [3]. Then we can notice that WICA is not more time-consuming, since it consists in a wavelet decomposition stage and an independent component analysis stage, as the other technique. Future efforts could be devoted to P and T waves extraction via WICA method and to improve the reliability of Q and S waves extraction, moreover, we could focus on automatic fECG extraction, since it would be a very useful real application for the fetus surveillance during labour.

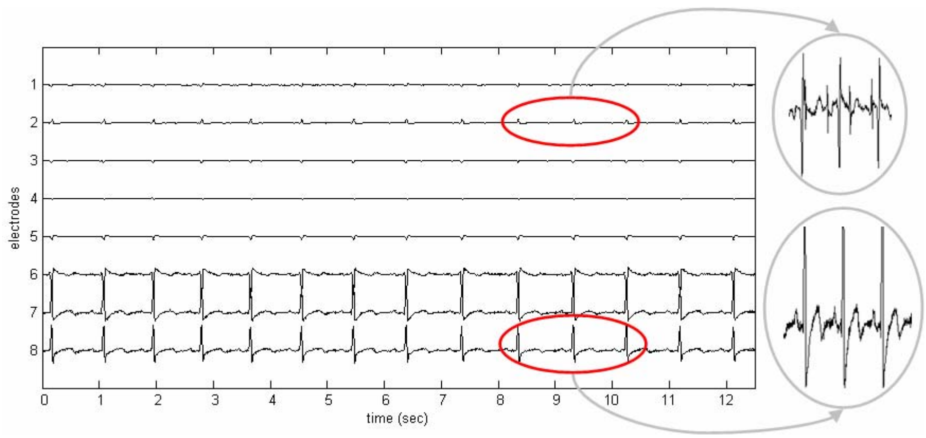

Figure 3: The eight channels mother abdominal and thoracic recordings.

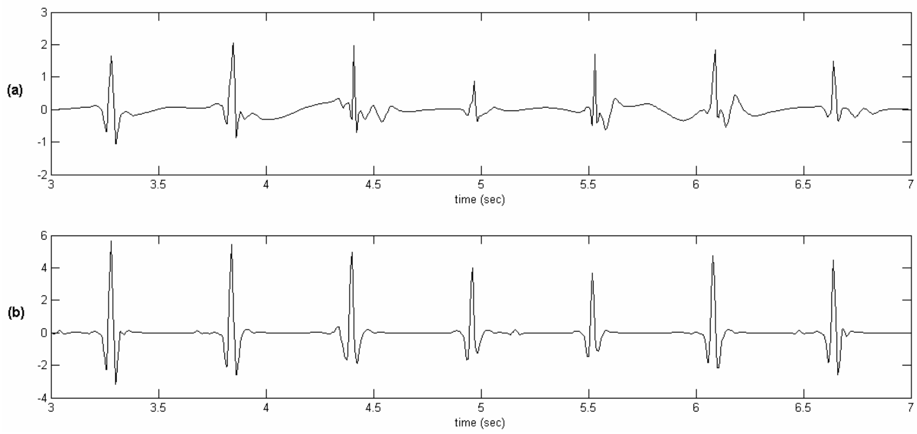

Figure 4: A zoom of the extracted fECG (a) by ICA and wavelet denoising and baseline removal, (b) by WICA method.

4 Conclusions

In this paper a recently developed method, WICA, was fitted to fECG extraction. This method showed to provide a clean signal accounting for fECG and to outperform the other techniques, since the reliability of Q, R and S waves extraction is improved with no need of any PQRST amplification. Q, R and S waves are visible and, in the future, we aim to focus on the P and T waves extraction and on the improving of the Q and S waves extraction reliability. We have also discussed how WICA procedure improves the quality of separation, indeed we have pointed out that wavelets are not exploited as a merely pre- or post-processing tool, but that the wavelet decomposition is an integral part of the separation process. We aim to address our future research on PQRST complex extraction and on automatic fECG extraction.

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