A New Algorithm for Fetal QRS Detection in Abdominal Recordings

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Abstract. The acquisition and the analysis of electrophysiological signals are often followed by the detection of parameters of clinical importance. In the case of fetal electrocardiogram signal, the presence of QRS complex is the best indicator of the fetal heart rate, as it is directly correlated with the fetal cardiac activity. However, to detect this complex, it is necessary to separate the signal from the maternal ECG signal. In this paper, a new algorithm for the fetal QRS detection is presented. This algorithm is based on two methods: the blind source separation method and the empirical mode decomposition (EMD) method.
The results obtained by the application of this algorithm to recordings of fetal electrocardiogram signals from the DaISy database show its good performance.

Keywords: fetal electrocardiogram, independence, blind source separation, empirical mode decomposition, DaISy database

1 Introduction

The fetal monitoring is an act of clinical importance because it can extract important information about the fetus and therefore detect anomalies reflecting the state of fetal well-being or distress. Doppler ultrasound [1] is one of the methods used in clinical routine. However, this technique is not suitable for long-term monitoring because it can have difficulties to adapt to changes in the fetal heart rate and uterine contractions [2].

Another technique used for fetal monitoring is the fetal electrocardiogram FECG. This is an invasive technique [3], since the electrodes are in direct contact with the fetal scalp. However, it cannot be used except in the latent phase (Cervical dilation, Amniorrhexis or rupture of the amniotic sac) and the cephalic position for the fetus.

For a long-term monitoring and during any period of gestation, it is preferable to use non-invasive fetal electrocardiogram [4] using abdominal and thoracic electrodes. The signals picked up by this method are strongly affected by various sources of noise, such as the maternal electrocardiogram, respiratory activity, the stomach activity, the thermal noise, the skin-electrode noise... etc. Therefore, the detection of QRS complex and other parameters of clinical interest is a real problem.

In this context, and to detect the QRS complex in the fetal abdominal recordings, we propose in this paper a system based primarily on the blind source separation, and then on the empirical mode decomposition. The algorithm is implemented and tested on the DaISy database signals. The obtained results show a good performance in QRS complex detection.

The rest of this paper is organized as follows. At first, the blind source separation is presented in section 2. In section 3, we briefly describe the empirical mode decomposition and also the algorithm of the fetal QRS detection. The results are presented in section 4. Finally, conclusions are presented in section 5.

2 Blind Source Separation

Zarzoso et al [5] and Lathauwer et al [6] showed that the detection of fetal electrocardiogram signal in the non-invasive method can be treated as a model of blind source separation BSS. The problem with this separation is to develop methods able to find N unknown sources observed through n known mixtures of these N sources.

The separation is called blind if we are able to separate the sources without any prior information on the sources and the mixture nature. Practically, it is impossible to solve the problem in this way. Therefore, to simplify the design and calculations, the following assumptions are made:

- The mixture is linear.
- N = n.
- The mixing coefficients are constant.
- The sources are independent.
- The sources are non-Gaussian except at most one.

These assumption lead to the most general equation given by:

$\mathrm{X} = \mathrm{A} * \mathrm{S}$ (1)

$X = (x_1, \dots, x_n)$: The observed signals.

$S = (s_1, \dots, s_n)$: The source signals.

A : The mixing matrix of n * n elements.

The goal is to find a separation matrix W of n*n elements, so that the transformed signals Y are statistically independent of each other as possible:

$\mathrm{Y(t)} = \mathrm{Wx(t)} = \mathrm{W} * \mathrm{A} * \mathrm{s(t)} \cong \mathrm{s(t)}$ (2)

Therefore W must be as close as possible to A^{-1}.

To solve this problem in the non invasive fetal electrocardiogram recordings, we chose to use the Fast Fixed-Point Algorithm for Independent Component Analysis [7].

3 Fast Fixed-Point ICA

The fast fixed-point algorithm for independent component analysis is based on the mutual information concept, since it is a natural measure of the dependence between random variables. Mutual information is based on the entropy and negentropy concepts.

Entropy is the basic concept of information theory. The entropy of a random variable can be interpreted as the degree of information that the observation of the variable gives. The more "random", i.e. unpredictable and unstructured the variable is, the larger its entropy [8]. The entropy H of a random vector y with density f is defined by:

$H(y) = -\int f(y) \log f(y) dy$ (3)

A fundamental result of the information theory is that a Gaussian variable has the largest entropy among all random variables of equal variance. To obtain a measure of nongaussianity that is zero for a Gaussian variable and always nonnegative, a normalized version of differential entropy, called negentropy is often used. The negentropy J is defined by:

$J(y) = H\left(y_{gauss}\right) - H(y)$ (4)

y_{gauss} is a Gaussian random variable of the same correlation matrix as y.

Using these concepts, we can define the mutual information I between n random variables y_i by [7]:

$I(y_1, y_2, \dots, y_n) = J(y) - \sum_i J(y_i)$ (5)

Then the separation matrix W is determined so that the mutual information of the transformed components Y are minimized. And since the negentropy is invariant for a linear transformation, it means that minimizing the mutual information is equivalent to maximize the negentropy.

In practice, the negentropy is approximated by:

$J(y_i) \approx c[E\{G(y_i)\} - E\{G(v)\}]^2$ (6)

Where G is a non-quadratic function, c is a constant, and v is a Gaussian variable with zero mean and unit variance.

First, to find an independent component as $y_i = W^T X$, we maximizes the function J_G given by:

$J_G(w) = [E\{G(W^T X)\} - E\{G(v)\}]^2$ (7)

Under the constraint of $E\{(W^T X)^2\} = 1$.

Using the approach of minimizing the mutual information, the contrast function described above can be simply extended to compute the whole matrix W. for this, and from (5), the mutual information is minimized (under the decorrelation constraint) when the sum of the components negentropies is minimized. So we define our estimator ICA by an optimization problem.

This method is applied on the daISy database signals available on the website: http://homes.esat.kuleuven.be/~smc/daisyi/ (Fig. 1).

This database contains five abdominal recordings and three thoracic recordings. The separation results are shown in Fig. 2.

After this application, we obtained a separation of fetal electrocardiogram from other interference. We observe that the first signal is the signal of interest. The QRS detection from the separated signal is obtained by a simple algorithm based on the empirical mode decomposition.

4 Empirical Mode Decomposition

The empirical mode decomposition EMD considers the oscillations of a signal at the local level [9] [10]; it splits the signal into two parts: the high frequencies and the low frequencies. First, it eliminates the low frequencies to isolate high frequencies. The first extracted signal is called the first intrinsic mode function IMF. Then, we iterate on the residue.

We equate the term of low frequency to the average between upper and lower envelopes of the signal. These envelopes are calculated by interpolating between the minimum (for the lower envelope) and the maximum (for the upper envelope) of signal.

It is assumed that all modes (IMFs) are extracted when the signal has one extrema.

The property of this method is that the IMFs are based on and derived from data. Therefore, this method is adaptive and therefore effective.

The EMD is applied to the first electrocardiogram obtained by the blind source separation (see Fig. 3).

The developed algorithm for the QRS detection from the obtained IMFs is as follows:

4.1 R Peak Identification

It is obtained by:

- Summation of the first three IMFs.
- Nonlinear transformation.
- Amplitude threshold.
- Temporal threshold.

4.2 Temporal Location of QRS Complexes

From a comparison between the original signal and the signal corresponding to the sum of the first three IMFs, we can say that the QRS complex can be determined by the zero crossing points of the right and left side of the signal of the sum of the first three IMFs.

The detected fetal QRS are shown in Fig. 4.

5 Results

Our study on the recovery of fetal electrocardiogram signal is based on the blind source separation BSS. This method can be applied with various ways; among them we used "Fast *Fixed Point* Algorithm for *Independent Component Analysis*". This method gives good results when we applied it to the signals of the daISy database (Fig. 1, 2).

After this success for the recovery of fetal electrocardiogram signal, we used an algorithm for QRS detection based on the empirical mode decomposition EMD. This method which is adaptive allows splitting the FECG signal with a specific base into different modes called IMFs (Fig. 3). Thanks to an algorithm applied to the IMFs, we obtained the QRS complexes (Fig. 4), which are the best indicator of the fetal heartbeat.

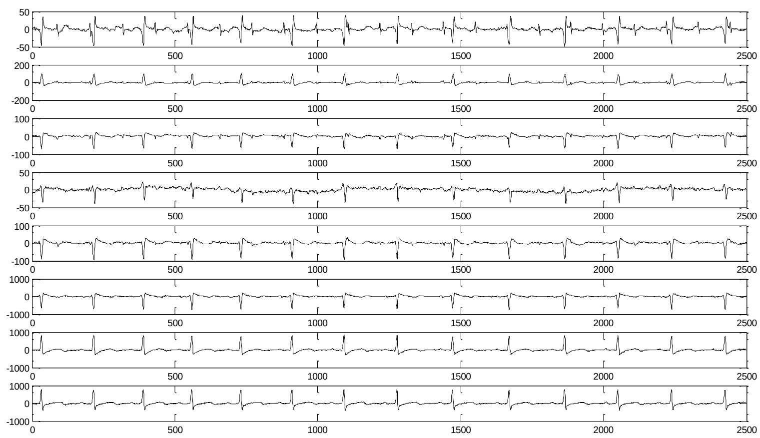

Fig. 1. The DaISy database Signals.

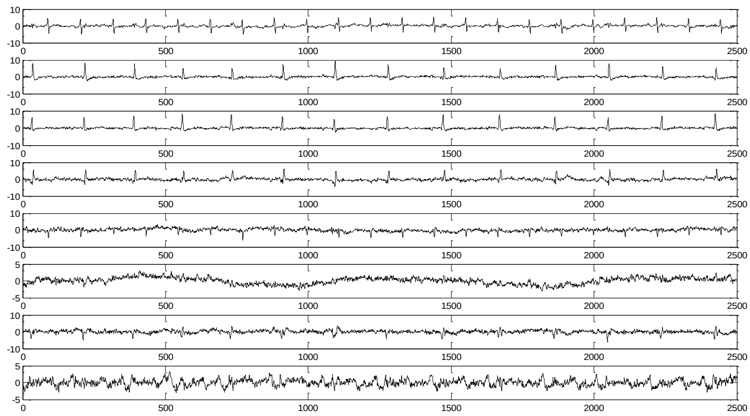

Fig. 2. The results obtained by the application of the fixed point ICA to the DaISy database Signals.

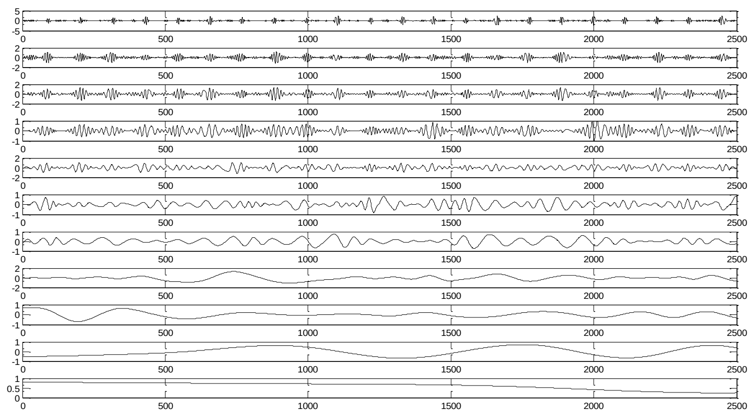

Fig. 3. The IMFs obtained by the application of the EMD to the FECG.

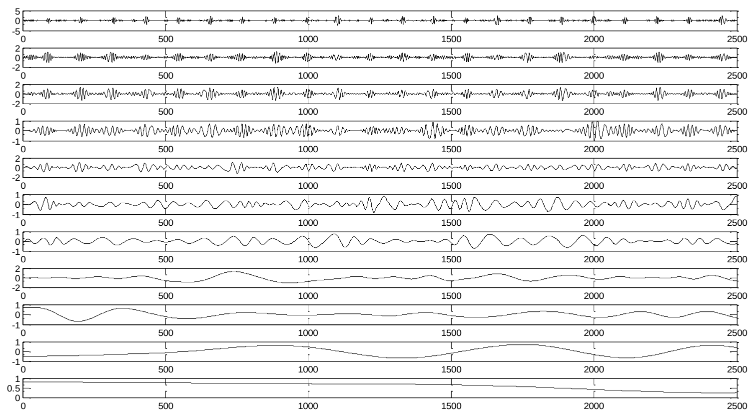

Fig. 4. The IMFs obtained by the application of the EMD to the FECG.

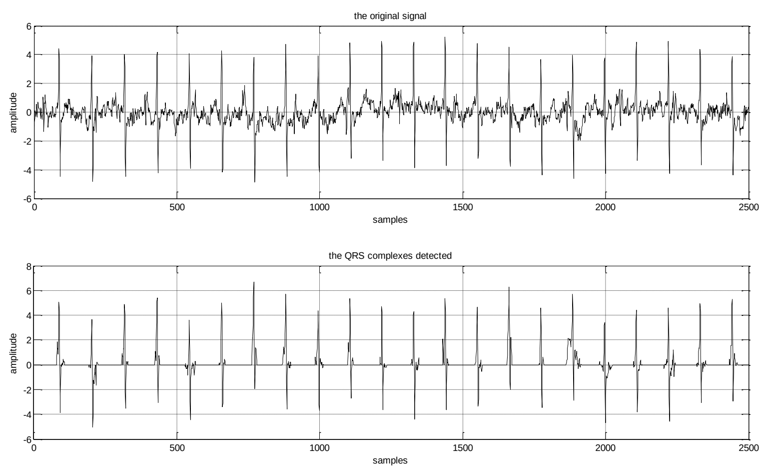

Fig. 5. The FECG and the QRS complexes detected.

6 Conclusion

In this paper, a new algorithm is discussed and evaluated for the recovery of fetal ECG signal and detect its QRS complexes. The key point of this approach is the application of the blind source separation to obtain an FECG signal separated from interference. Then we tried by the empirical mode decomposition to detect the QRS complexes which are the best indicator of a heartbeat.

The application of these two methods on real signals of DaISy database provides qualitatively good results.

Also, we give as prospects for this algorithm: reducing the electrodes number and study of noisy signals of other databases. Also, the analysis can be performed for the detection of other parameters such as the ST segment.

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