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Improvement of the Fetal Electrocardiogram Signals

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Abstract: -The health of the fetus is of major concern to both obstetricians and expectant mothers. A non-invasive fetal electrocardiogram (FECG) system can monitor fetal cardiac condition during pregnancy. However, the FECG signal is often very weak or drowned out by the mother's ECG (MECG) and other noises. This study uses a FastICA algorithm to the isolate FECG signal from other noise interference. The results show that such mixed signals can be separated by FastICA into MECG, FECG, and noises, thus enabling obstetrician to clearly understand the fetal condition through FECG monitoring.

Key-Words: - Signal processing, ICA, FECG

1 Introduction

Fetal electrocardiogram (FECG) signals, such as the fetal heart rate, T/QRS amplitude ratio and locomotor activities, allow obstetricians to monitor fetal vital signs and maturity during pregnancy. With the help of FECG, obstetricians can check on fetal growth, detect congenital cardiovascular diseases and identify any possible factors indicating aplasia. This makes FECG an important index in clinical practices. However, its signal-noise ratio (SNR) is often very low, because the FECG signal is very weak and is usually interfered by with the mothers ECG (MECG) and other noises. Therefore, reducing the extraneous noise in FECG is essential for the correct diagnosis of the fetal condition. In this study, we use FastICA to separate the FECG from other noises and to improve the quality of the FECG signals.

Independent Component Analysis (ICA) is a technique that combines statistics, computational simulation and digital signal processing [1],[2]. It can reveal the hidden sources that underlie sets of mixed signals. In 1986, Herault and Jutten presented a recurrent neural network model and a simple feedback adaptive algorithm that was able to blindly separate mixtures of independent signals [3]. This method was further developed by Jutten and Herault (1991), Karhunen and Joutsensalo (1994), Cichocki, and Unbehauen and Rummert (1994) [4]-[6]. In 1994, Comon outlined the general framework for ICA introduced by Herault and Jutten with greater clarity and in more theoretical detail. He also developed an objective function based on cumulant in statistics [7]. Linsker (1992) proposed an unsupervised learning rule based on information principles [8]. Its primary purpose was to allow maximization of the information shared by the input and the output of a neural network. Bell and Sejnowski (1995) derived a learning rule which could perform a gradient ascent on the information content of the network [9]. This is considered a more successful method than Comon's (1994) for information maximization [10]. At present, there are two main types of ICA: InfomaxICA developed by Lee (1998) and FastICA by Hyvärinen (1999) [11]-[15]. FastICA was derived from quasi-neural network learning rules. It uses a fixed-point iteration scheme, faster than the conventional gradient descent methods, for ICA.

This study explains why ICA can be applied to FECG. ICA can be used to isolate the original independent sources in a set of mixed signals. (For instance, a mixed signal could consist of three original signals. ICA can help identify each of the tree signals independently.) Traditional FECG systems often received mixed signals from fetal heart beat, mother's heart beat, and other noises, causing difficulty in monitoring fetal health. The use of ICA can improve the quality of FECG signals and ensure accurate understanding of fetal condition. Other means of improving FECG quality have been tested in previous studies [18]-[22].However, none of these means is as simple and effective as ICA.

2 FastICA Theory

ICA is a new statistical technique that has been developed in recent years [1]-[10]. Here we define the observed data $\mathbf{x} = (x_1, x_2, \ldots x_m)^T$ as random variables in a single m dimension. Like the diverse signals recorded by the perceptron, the signals can be measured by

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

where $\mathbf{s} = (s_1, s_2, \ldots s_n)^T$ is the latent variable (independent component) and $\mathbf{A}$ denotes the mixing matrix. Generally speaking, ICA looks for a linear transformation like the following:

$$\mathbf{y} = \mathbf{w}\mathbf{x}, \tag{2}$$

where $\mathbf{y}$ denotes the estimated value of the independent component $\mathbf{s}$; $\mathbf{w}$ represents an unmixing matrix. The purpose is to make the $\mathbf{y} = (y_1, y_2, \ldots y_n)^T$ between the components as independent as possible. In other words, if a measured independent function $f(y_1, y_2, \ldots y_n)$ is maximized, it will result in $\mathbf{w} = \mathbf{A}^{-1}$. So, $\mathbf{y} = (y_1, y_2, \ldots y_n)^T$, processed by ICA, will be equal to the original latent variable, $\mathbf{s} = (s_1, s_2, \ldots s_n)^T$ and $\mathbf{w}$ is the matrix sought, with the dimensions of $n \times m$. The goal of ICA is to find a linear transformation $\mathbf{w}$ of the dependent sensor signals $\mathbf{x}$ that makes the outputs as independent as possible

$$\mathbf{u} = \mathbf{w}\mathbf{x}, \tag{3}$$

where $\mathbf{u}$ is an estimate of the sources. The objective is to minimize the statistical dependence between the components. An illustration on ICA is shown in Fig. 1.

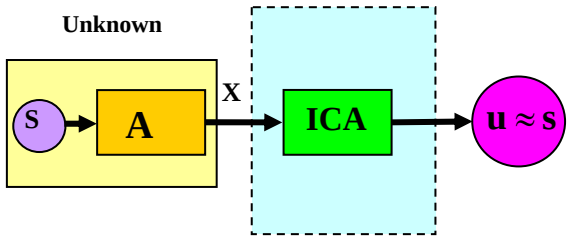

Fig. 1 Sketch of independent component analysis.

To identify the correct $\mathbf{w}$, the following function approximation is developed based on the largest entropy principle:

$$J(\mathbf{y}) \propto [E\{G(\mathbf{y})\} - E\{G(v)\}]^2, \tag{4}$$

where G denotes a non-quadratic function and v stands for a gaussian random variable. Here, $G(y) = (1/a_1)\log\cosh a_1 y$, with $1 < a_1 < 2$. The mean of v is zero. The changing factor is the Gaussian random variable of 1. G can be any non-quadratic function without restriction, for which the value will be zero when G is a quadratic function. FastICA identifies independent components by maximizing the negentropy [11-15]. According to Hyvärinen, the largest J values in $E\{G(\mathbf{w}^T\mathbf{x})G(\mathbf{y})\}$ of Eq.(4) can be attained at certain optima of $E\{G(\mathbf{w}^T\mathbf{x})\}$. Under the delimitation of $E\{(\mathbf{w}^T\mathbf{x})^2\} = \|\mathbf{w}\|^2 = 1$, the optima of $E\{G(\mathbf{w}^T\mathbf{x})\}$ will appear in

$$E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - \beta\mathbf{w} = 0, \tag{5}$$

Here, we use Newton's method to solve the above equation. If we replace the left end of Eq.(5) with $F(\mathbf{w})$ and the Jacobian matrix with $JF(\mathbf{w})$, then Eq.(5) becomes the partial differential of $\mathbf{w}$.

$$JF(\mathbf{w}) = E\{\mathbf{x}\mathbf{x}^T g'(\mathbf{w}\mathbf{x})\} - \beta\mathbf{I}, \tag{6}$$

Newton's method looks for the extent of modification in $\mathbf{w}$, for each time. The relation is presented as follows:

$$JF(\mathbf{w})\Delta\mathbf{w} = -F(\mathbf{w}), \tag{7}$$

To determine the extent of the modification in $\mathbf{w}$ for each time, we need to calculate the inverse matrix of $JF(\mathbf{w})$. To simplify the calculation, on approximation of the first item in Eq.(7) is processed. Since the data has been whitening, then

$$E\{\mathbf{x}\mathbf{x}^T g'(\mathbf{w}\mathbf{x})\} \approx E\{\mathbf{x}\mathbf{x}^T\} E\{g'(\mathbf{w}\mathbf{x})\} = E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{I} \tag{8}$$

Such an approximation is acceptable. The Jacobian matrix in Eq.(6) can now be diagonalized as

$$JF(\mathbf{w}) = [E\{g'(\mathbf{w}^T\mathbf{x}) - \beta\}\mathbf{I}, \tag{9}$$

It is new fairly simple to identify the inverse matrix. After the approximation in Eq.(9), the iteration of Newton's method results in the following form:

$$\begin{aligned}\mathbf{w}^+ &= \mathbf{w} + \Delta\mathbf{w} \\ &= \mathbf{w} - [E\{\mathbf{x}g'(\mathbf{w}^T\mathbf{x}) - \beta\mathbf{w}\}]/[E\{g'(\mathbf{w}^T\mathbf{x}) - \beta\}] \\ \mathbf{w}^* &= \mathbf{w}^+ / \|\mathbf{w}^+\|.\end{aligned} \tag{10}$$

This algorithm can be further simplified. If both ends of Eq.(10) are multiplied by $\beta - E\{g'(\mathbf{w}^T\mathbf{x})\}$, the fixed-point iteration scheme is renewed as

$$\begin{aligned}\mathbf{w} &= E\{\mathbf{x}g'(\mathbf{w}^T\mathbf{x})\} - E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}, \\ \mathbf{w} &= \mathbf{w}^* / \|\mathbf{w}^*\|.\end{aligned} \tag{11}$$

Finally, the condition for convergence requires that the old vector w and the new vector $\mathbf{w}^+$ be parallel, but not necessarily directed at the same point. Since $\mathbf{w}$ and $\mathbf{w}^+$ are parallel, the convergence will identify the independent components, when the inner absolute value of both vectors is 1.

3 Results and Discussion

Figure 1 shows seven ECG signals recorded from the bellies of pregnant women for 5 seconds. The first trace from the top down shows the mixed MECG and FECG signals. The other traces indicate MECG signals or noise. The maternal heart beat can be observed as 14 beats within 5 seconds, however, the fetal heart beat is unobservable. Herein, this characterization will be performed via a time-frequency representation, which has the advantage that it can be easily constrained to yield the real distributions, which can be interpreted as the two dimensional decomposition of a signal's energy [16],[17]. Figure 3 presents the time-frequency analysis of the mixed MECG and FECG signals in Figure 2. The horizontal axis shows time progression; the vertical axis indicates the frequency domain. The color spectrum denotes the signal volumes in dB. In Figure 3, the margin between high frequency and low frequency is 225 Hz. Low frequency signals require higher energy and are therefore presented in red. High frequency signals, on the other hand, are in blue or green. The changes in the signals are here clearly observable. Since both MECG and FECG are below 225 Hz, that is in the low frequency range, it is not possible to separate them with a classical filter. An adaptive filter can cancel out the MECG signal, but the remaining noise continues to interfere with FECG signal. In this study, we use FastICA to identify the mixed matrix w and reconstruct the seven ECG signals. Figure 4 shows the reconstructed ECG signals. The MECG, FECG signals and the noise can all be clearly identified. The Fetal hear beat can be observed as 22 beats per 5 seconds. Figure 5 illustrates time-frequency analysis of FECG signals. In Figure 5, low frequency signals processed by FastICA are shown in red and orange stripes. Since MECG has been separated, the time-frequency features of FECG can be clearly understood. Figure 6 presents the time-frequency analysis of the MECG signals. Using these procedures, we find that FastICA can separate the confused mixed signals, to enable an obstetricians to better monitor fetal health.

FastICA uses Newton's method, a classical numerical analysis that optimizes the mixed matrix by the iteration of linear equations. It does not require learning rate as a parameter. This makes FastICA much more easily accepted by the users. Moreover, FECG requires an algorithm with fast convergence speed. Hyvärinen A. compared FastICA and stochastic gradient employed in information maximization approach, with the best learning rate sequence in quasi-neural network. The results showed that flops in FastICA is only 10% of stochastic gradient. If the learning rate sequence was chosen in an trail-and-error manner without preliminary processing, the convergence speed of fixed point algorithm will be 10^2 integer times faster than the series and stochastic gradient might not lead to convergence. Therefore, FastICA is more suitable for processing FECG signals.

We hope this study will lead to a complete non-invasive FECG system in the future, recording signals from the abdomen of pregnant women. However, there are some problems yet to be solved. First of all, the fetus can change positions in the mother's uterus. It's difficult to record the signals at the specific site. Secondly, because blocking of amniotic fluid, uterus, muscles, fat, and skin of mother, FECG signals are very weak. Clear FECG signals can be obtained from the mother's abdomen only after 20 weeks of gestation. The improvement in signal detection technique is a significant contribution to the analysis of FECG signals. The high resolution of FECG signals allow better evaluation of fetal health.

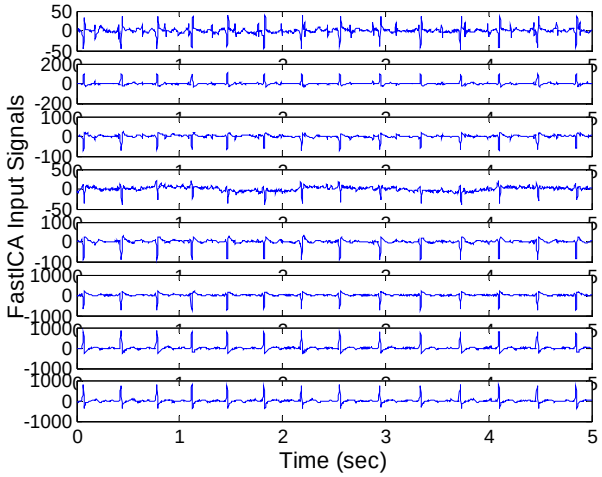

Fig. 2 Seven MECG signals recorded form the bellies of pregnant women.

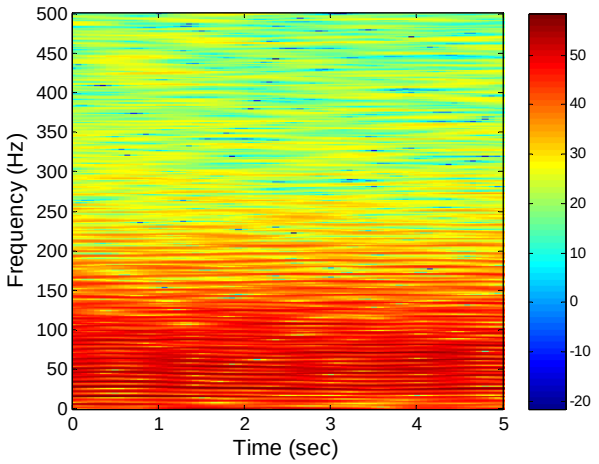

Fig. 3 Time-frequency analysis of the mixed MECG and FECG signals.

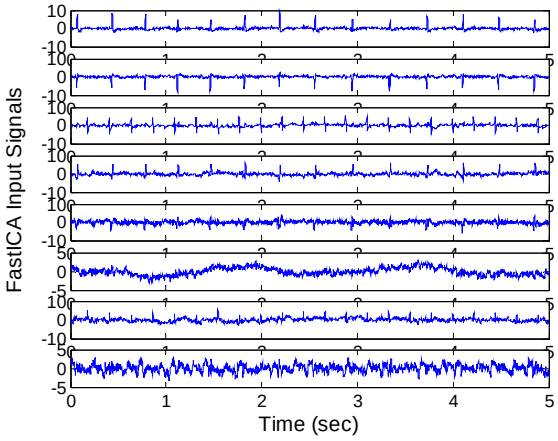

Fig. 4 ECG signals processed by the FastICA.

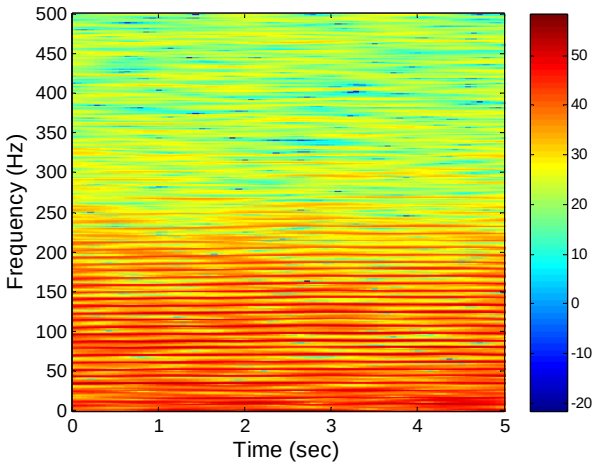

Fig. 5 Time-frequency analysis of the FECG signals.

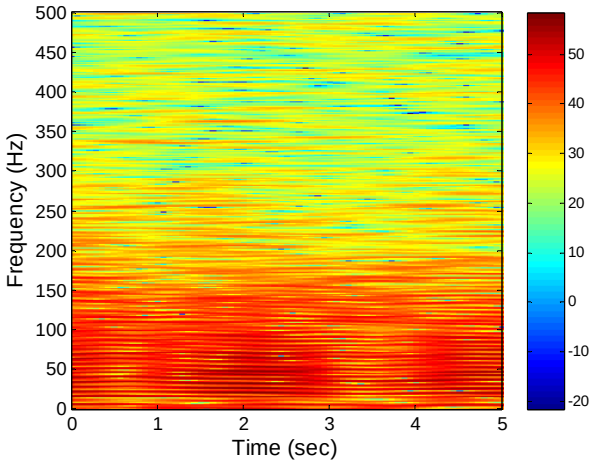

Fig. 6 Time-frequency analysis of the MECG signals.

4 Conclusion

This study is aimed at using FastICA in improve the quality of FECG signals. After being processed by FastICA, the fetal heart beat signals can be clearly detected. Our study proves that FastICA can be an important technique in clinical applications for : (a) monitoring the vital signs of the fetus in the mid late gestation periods; (b) early diagnosis of multiple pregnancies; (c) detecting irregular heart rhythms; (d) monitoring fetal heart beat during delivery; (e) detecting fetal presentation. Although other equipment such as ultrasonographs and phonocardiographs may provide some of these functions, only the FECG can help monitor fetal cardiac charge signals and detect anomalies as early as possible.

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