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# Performance Comparison Research of the FECG Signal Separation Based on the BSS Algorithm

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**Abstract:** Fetal Electrocardiogram (FECG) is a weak signal through placing the electrodes upon the maternal belly surface to indirectly monitor, which contains all the forms of jamming signal. So, how to separate the FECG from the strong background interference has important value of clinical application. Independent Component Analysis (ICA) is a kind of developed new Blind Source Separation (BSS) technology in recent years. This study adopted ICA method to the extraction of FECG and carried out the blind signal separation by using the Fast ICA algorithm and natural gradient algorithm in the FECG separation research. The experimental results shown that the two kind of algorithm can obtain the good separation result. But because the natural gradient algorithm can achieve FECG online separation and separation effect is better than Fast ICA algorithm, therefore, the natural gradient algorithm is a better way to used in FECG separation. And it will help to monitor the congenital heart disease, neonatal arrhythmia, intrauterine fetal retardation and other diseases, which has very important test application value.

**Keywords:** Blind signal separation, fast ICA, FECG, ICA, MECG

## INTRODUCTION

FECG adopts noninvasive monitoring way (Lee *et al*., 2006; Wan *et al*., 2006) to record the fetal heart action potential in the heart of the conduction process and its graphics changes, which is one of the objective indicator reflecting the fetal safety conditions in maternal uterine.Iit can be found that the fetal early intrauterine hypoxia, distress, for many fetal diseases, such as congenital heart disease, neonatal arrhythmia, intrauterine fetal retardation, etc. FECG is collected from the maternal belly, in the process of collecting the signal, inevitably, it will contain a lot of noise (such as power frequency interference, a Maternal Electrocardiogram (MECG). Arie (2000) So, separating the FECG from the mixed MECG is basic problem. The traditional fetal ecg separation methods include the adaptive filter technology, space filtering method, Singular Value Decomposition (SVD) method, etc. Jutten and Herault (1996).

The signal collection demand to these methods is higher; the fetal position, maternal status and movation are highly sensitive, as well as the processing of real-time is relatively poor. This study uses the ICA method to separate the FECG and adopts the Fast ICA and natural gradient algorithm to carry out the signal blind separation. Through the experiment and comparing this two algorithm, which verifies the natural gradient algorithm is superior to the Fast ICA in the blind source separation.

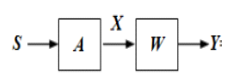


Fig. 1: ICA model frame diagram

**Introduction of ICA:** Independent Component Analysis (ICA) was originally used to solve the ocktail party problem as in condition of many persons' voices of mutual aliasing, required to let the speech separated alone. ICA is to point to the source signal only using source signals' observation (mixed) signals to restore the each independent component of source signal. Figure 1 expresses independent component analysis problem with the structure diagram. Bi (2007)

If we suggest $x(t) = [x_1(t), x_2(t),\ldots, x_n(t)]^T$ is *n* dimension random observation mixed signal, now, there is *m* numbers of source signal $s(t) = [s_1(t), s_2(t), \ldots, s_m(t)]$ T, each observation value $x_i(t)$ is a sampling of the random variable, which has general character, a mixture of general stochastic variable and independent sources have zero mean. When we define the ICA model in the matrix form, $X = (x_1, x_2, \ldots, x_n)^T$ is *n* random observation vector, $S = (s_1, s_2,\ldots, s_m)^T$ is *m* dimension unknown source signal, then the ICA linear model can be expressed as formula (1):

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$$X = AS = \sum_{j=1}^{m} a_i s_i(t),\ i = 1, 2, \ldots, m \qquad (1)$$

Among the formula (1), $s_i(t)$ is an independent component, $A = (a_1, a_2, \ldots, a_m)$ is a $m \times n$ full rank mixed matrix and $\alpha_i$ is base vector matrix of mixed matrix. From the formula (1) we can see, each observation data $x_i(t)$ is gotten by the different linear weight of $a_{ij}$ by independent source $s_i(t)$. The Independent source $s_i(t)$ is implied variables, without the directly measured. Mixing matrix *A* is an unknown matrix and the information that can be adopted only the observation of the random vector *X*. Without restriction conditions, only *X* estimate *S* and *A*, there are countless equation solution. In ICA model, the source signals need independent and must satisfy the non-Gaussian distribution characteristics. In order to simplify the mathematical model, we assume the unknown mixture matrix *A* is a square formation of $m = n$. So that the purpose of the ICA would need to find a transformation matrix and transform *X* in linear to get *n* output vector Y:

$$Y = WX = WAS \qquad (2)$$

**Fast ICA algorithm:** Fast ICA algorithm is based on the maximum principle of non-Gaussian character, uses fixed-point iterative theory to look for non-Gussian character maximum of $W^T x$, this algorithm adopts Newton iterative algorithm and carries out batch to amount of sampling points of observed variables *x*, isolates a independent component from observation signal every times. In order to reduce the estimate parameters of the algorithm and simplify the calculation of algorithm, before running Fast ICA algorithm, we need carry out data pretreatment, that is removing mean value and bleaching process. The solving process of the Fast ICA algorithm is shown as bellow: (Jutten and Herault, 1996):

- Randomly selecting chosen initialized weights vector $w_0$ and k = 0
- Using formula $w_{k+1} = w_{K+1} - \sum_{j=1}^{k} w_{K+1}{}^T w^j w^j$ , $w_{k+1} = w_{K+1} / \sqrt{w_{K+1}{}^T w_{K+1}}$ to update weights vector $w_{K+1}$:
- Normalized $w_{K+1}$ and $w_{k+1} = w_{k+1}/\|w_{k+1}\|$
- If $|w_{k+1}-w_K|>\epsilon$, then the algorithm is not convergence, return, or Fast ICA algorithm estimate a independent component and the algorithm is over

**Natural gradient algorithm simulation:** In Euclidean space, the gradient of the cost function *L*(*W*) relative to the separation matrix *W* is shown as formula (3):

$$\nabla L(W) = W^{-T} - E\{g(y))x^T\} \qquad (3)$$

Among the formula (3), $W^{-T}$ is an inverse matrix. E{.} is an expectations. $y_i$is the *i* number output component. $p(y_i)$ is probability density function of $y_i$. $p(y^i)$ is the derivative of $p(y_i)$. So, the non-linear function is shown as formula (4):

$$g(y_i) = \frac{-p(y_i)'}{p(y_i)} \qquad (4)$$

To make the mathematical expectation of cost function *L*(*W*) minimize, we often make use of the instantaneous of the random variables instead of the expectations and get following online learning algorithm of conventional randomized gradient descent.

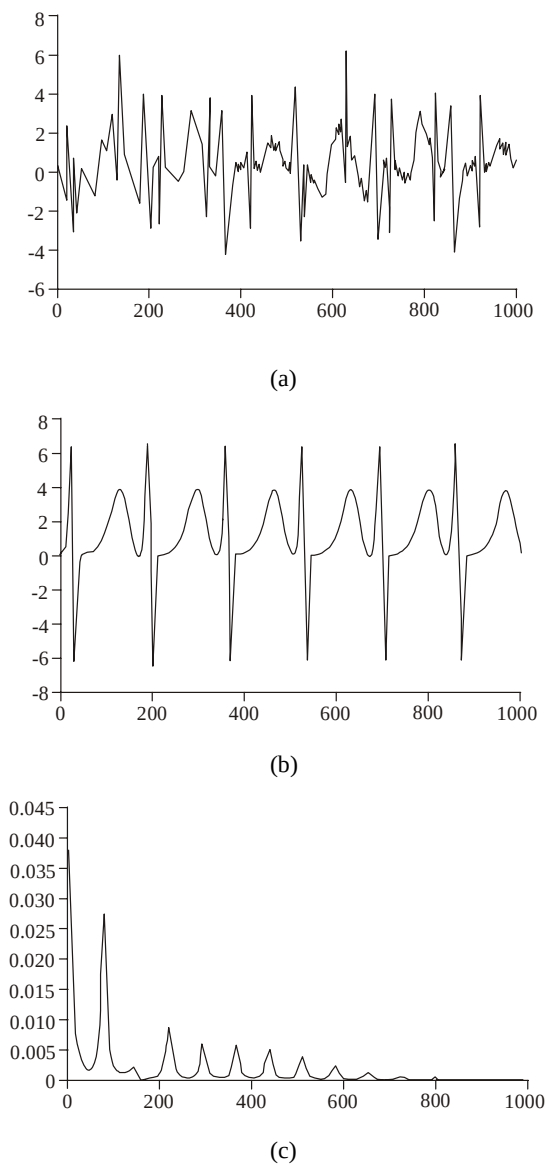


Fig. 2: Source signal waveform

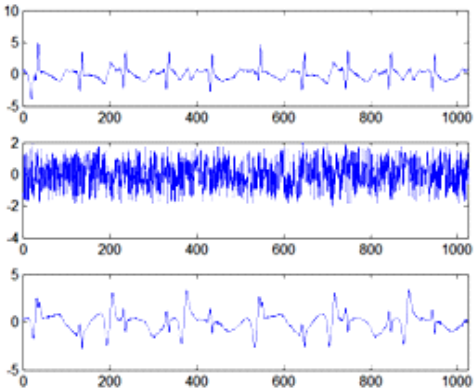

Fig. 3: Separation signals by using fast ICA algorithm

$$\nabla W=u(k+1)(W^{-T}(k)-g(y(k))x^{T}(k)) \quad (5)$$

Among formula (4), u is the step length of algorithm and u<<1. The randomized gradient $\nabla L(W)$ of formula (4) expresses the steepest reduce direction of the Euclidean space cost function L(W). Amari etc. prove the nature gradient $\tilde{\nabla} L(W)$ is the steepest drop direction in Riemann space of parameters W, but not the random gradient $\nabla L(W)$. The natural gradient $\tilde{\nabla} L(W)$ can be calculated by modifying the random gradient, which is gotten through right multiplying $W^{T}W$ in the random gradient:

$$\tilde{\nabla} L(W) = [I-E\{g(y)y^{T}\}]W \quad (6)$$

So, we can get online nature gradient learning algorithm, which is shown as formula (7). (Amari *et al.*, 1995):

$$\nabla W = u(k+1)(I-g(y(k))y^{T}(k))W(k) \quad (7)$$

**BSS algorithm application:** The realization of BSS algorithm includes three points:

- Removing mean value of the observation signal
- Bleaching processing to the observation signal after mean processing
- The process of independent components extraction algorithm and realization.

Figure 2a is the source signal of observation collection ecg consisted of the fetal ecg, mothernal ecg and the noise signal, etc, Fig. 2b is the mothernal FECG signal and Fig. 2c is the frequency spectrum of the MECG.

**Fast ICA algorithm simulation:** We suggest the observation signal containing the fetal ecg, mothernal ecg and the noise signal, etc, the results by using Fast ICA separation algorithm to separate the source signals are shown as Fig. 3.

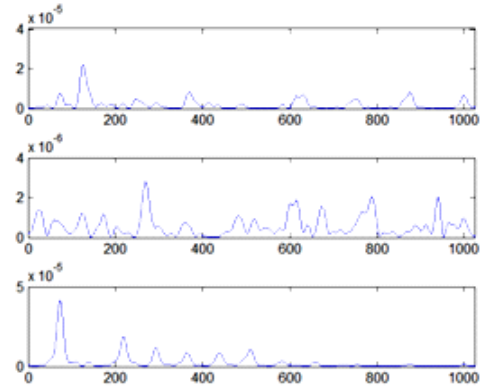

Fig. 4: Frequency spectrum of the separation signals by using fast ICA algorithm

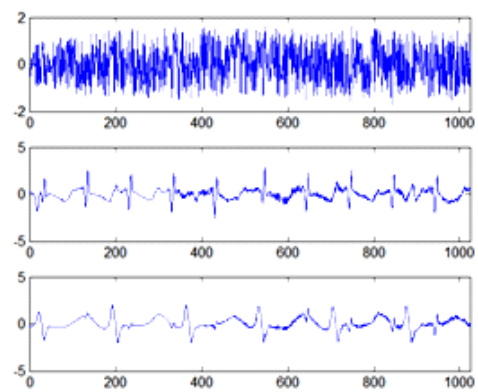

Fig. 5: Separation signals by using natrual gradient algorithm

From the Fig. 3 we can see, three signals respectively is the fetal ecg, mothernal ecg and the noise signal. Among them,

- Is FECG
- Is the noise signal
- Is MECG

But, the MECG contains the FECG component, which expresses the Fast ICA algorithm can not separate the mixed signal well. Although the separation signal by using the Fast ICA BSS algorithm have gained the better effect, we can see the MECG signal contains the FECG signal. The frequency spectrum of the separation signal is shown as Fig. 4.

From the Fig. 4, we can see the frequency characters of the signal.

- Is the FECG signal
- Is the noise signal
- Is the MECG signal

**Natural gradient algorithm simulation:** We carry out the signal sepration by using the natural gradient

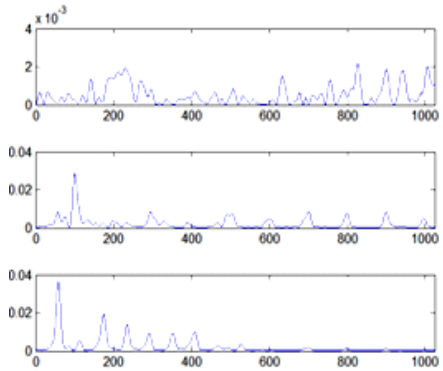


Fig. 6: Separation signals by using natrual gradient algorithm

Table 1: Mothernal heart-beat position comparation between separated signal and source signal

| Mothernal ECG value | Source signal (sampling point) | Fast ICA (sampling point) | Natrual gradient (sampling point) |
|---|---|---|---|
| 1 | 22 | 22 | 22 |
| 2 | 193 | 193 | 193 |
| 3 | 365 | 364 | 365 |
| 4 | 534 | 532 | 534 |
| 5 | 705 | 705 | 705 |
| 6 | 877 | 877 | 877 |

algorithm and the blind separation result is shown as Fig. 5.
among them,

- Is the noise signal
- Is FECG
- Is MECG

We can see from the graph, the fetal and the maternala signal is effective separation, but the MECG and FECG still have part of the noise signal. But from MECG we can find, the separation MECG is effectively closer to the actual MECG, which is better than the Fast ICA separation algorithm. And the separation signal frequency spectrum is shown as Fig. 6.

**Algorithm analysis and comparation:** From the maternal ecg signals we can measure the position of each heart beating and we compare the Fast ICA separation algorithm with the natural gradient algorithm, the result is shown as Table 1.

From the separation result, comparing the Fast ICA and natrual gradient with the actual MECG. Using the Fast ICA algorithm and natural gradient algorithm all can get more accurately separation signal. The two algorithm of the separation heart beating position is shown as Table 2.

- From the Table 2 we can see, the FECG separation result is basic same to the source signal and the two kinds of the separation algorithm verified the separation efficiency each other.

Table 2: Fetal heart-beat position comparation between separated signal and source signal

| Fetal ECG value | Separated signal (sampling point) | Fast ICA (sampling point) | Natrual gradient (sampling point) |
|---|---|---|---|
| 1′ | 18 | 19 | 18 |
| 2′ | 130 | 130 | 129 |
| 3′ | 230 | 231 | 229 |
| 4′ | 331 | 330 | 330 |
| 5′ | 431 | 430 | 431 |
| 6′ | 542 | 542 | 542 |
| 7′ | 643 | 642 | 642 |
| 8′ | 742 | 743 | 741 |
| 9′ | 843 | 842 | 843 |
| 10′ | 942 | 943 | 943 |

- From the Fig. 3 and 5, we can see, the separation signal are basic consistent, but by using the Fast ICA algorithm, the separation signal of MECG consist the FECG, the noise signal is separated well. By using the natural gradient algorithm, the signal separation effect is good, but the noise signal still consist in their respective signal and the MECG separation effect is better than the Fact ICA algorithm, which does not consist the FECG signal.
- Frome the Fig. 4 and 6, we can see, there are responsing advantage in the frequency spectrum. By using the Fast ICA algorithm of Fig. 4, the frequency spectrum of MECG is completely same with the source MECG in Fig. 2c, but the frequency spectrum of MECG has other frequency character of 160 Hz in Fig. 6. So, the two kinds of BSS algorithm each have their own separate superiority.

## CONCLUSION

This study detailed study the bind signal separation algroithm, through using the Fast ICA algorithm and natrunal gradient algorithm, we can get FECG from the blind mixed ecg. The simulation result realizes the mixed signal sepration effectively. In addition, through compraing the two algorithm, due to the natural gradient algorithm is better than the Fast ICA algorithm, the natural gradient algorithm can realize online blind separaion, which can be applied to the clinical fetal disease monitoring and online protection.

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