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Research and Application of Fetal Electrocardiogram Blind Signal Separation Technology

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Abstract: FECG (Fetal Electrocardiogram) is weak signal indirect monitored between the electrode that placed upon the mother abdominal the matrix surface, which contains all the forms of jamming signal. How to separate the Fetal from the strong background interference has important value of clinical application, but this is a difficult problem in the signal processing field. Independent Component Analysis (ICA) is a kind of Blind Signal Separation (BBS) technology that not need to know prior signal. This study introduced the basic theory of ICA, discussed the application of ICA in the blind mixed FECG signal, given the information maximization (Informax) blind source separation algorithm and simluated the instantaneous mixed FECG signal. The experimental results show that this method can effectively improve the operation efficiency and achieve a good separation effect, the monitoring time error is less than 0.5% and the feature point frequency of spectrum diagram error is less than 1%.

Key words: FECG, blind source separation, ICA, informax, blind mixing signal

INTRODUCTION

FECG contains the fetal important information of health condition, which is a objective indicator reflecting the fetal heart activity. Through the FECG extraction of perinatal fetal, we can analyze and determine the fetal heart rate, judge whether the fetus in distress, multiple births and inspect the heart function parameter state, in order to prevent the neonatal disease (Zarzoso *et al.*, 1997). And in favour of finding the fetus hypoxia, umbilical cord around pregnancy or the pathological conditions during delivery, early taking the measures to ensure the fetal health, reducing the perinatal fetal morbidity and mortality. At present, the FECG acquisition method basically has two kinds: Fetal scalp electrode and maternal abdominal skin electrode. Fetal scalp electrode method will not only damage to the fetus, but also can not be used in pregnancy; Maternal abdominal skin electrode has the advantages of its convenient, noninvasive and can be used in pregnancy, which deeply get medical workers and pregnant women welcome (Groome *et al.*, 1999). Because the FECG is very weak and mixed with strong background noise, such as the Maternal ECG (MECG) signal, noise interference and so on, which brings more difficult to the FECG accurate extraction and analysis.

In recent decades, domestic and international experts and scholars have proposed many extraction method of FECGl, such as the adaptive noise cancellation technology (Liu *et al.*, 1985), singular value decomposition technique (Kanjilal *et al.*, 1997), wavelet transform, etc. (Khamene, 2000) But these methods have some limitation. In recent years, Independent Component Analysis (ICA) had caused the attention in the field of biomedical signal processing. ICA is a kind of new multidimensional statistical analysis method, its characteristic is that the individual source signal components can be recovered from the more road observation signal.

In this study, we discussed the nonlinear blind mixed ecg signals separation technology. We firstly introduced the model of the ICA algorithm and the implementation methods of information maximization (Informax) algorithm and then studied the establishment of the objective function and the realization of the algorithm. In addition, through the separation experiments of ECG blind mixed, we use the Informax algorithm to separate the mothernal and fetal ECG in higher precision, which proved this blind signal separation algorithm accuracy.

ICA MODEL

ICA was originally used to solve the cocktail party problem. 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.

If we suggest $x(t) = [x_1(t)\ x_2(t),...x_n(t)]^T$, is n dimension random observation mixed signal, now, there is m numbers of source signal $s(t) = [s_1(t) = s_2(t),...s_m(t)]^T$, 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

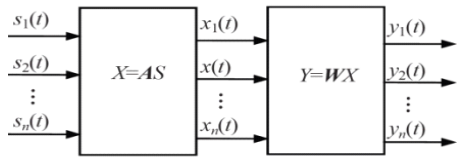

Fig. 1: ICA model frame diagram

matrix form. $X = (x_1, x_2, ... x_n)^T$ is n random observation vector. $S = (s_1, s_2, ... s_m)^T$ is m dimension unknown source signal, then the ICA linear model can be expressed as formula (1):

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

Among formula (1), $S_i(t)$ is independent component, $A = (a_1, a_2, ... a_m)$ is $m \times n$ full rank mixed matrix, a_i is base vector matrix of mixed matrix. From formula (1) we can see, each observation data $x_i(t)$ is gotten by different linear weighted of a_{ij} by independent source $S_i(t)$. Independent source S_i (t) is implied variables and they do not directly measured, mixing matrix A is also unknown matrix, the information that can be adopted only the observation of random vector X. Without restriction conditions, only X estimate S and A, there are countless equation solution. And in some limited conditions of ICA, according to the statistic characteristics of X, it given the only solution and realize the equation of independent component of the extraction. An important basic assumption of ICA is the requirements of independence character to unknown source signals. In ICA model, the source signals need independent, also must satisfy the non-Gaussian distribution characteristics, in addition, in order to simplify the mathematical model, we assume the unknown mixture matrix A is a square formation, which is $m = n$. So, that is the purpose of the ICA would need to find a transformation matrix, transform X in linear and get n output vector: $Y = WX = WAS$.

INFORMATION MAXIMIZATION CRITERION

The multivariable separation algorithm of ICA requests the output signal statistical independence as far as possible, so, ICA algorithm design is to build on the target function of the output variables independence measurement and then optimize the objective function, which searching for the optimal separation matrix (Zhu and Zhang, 2003). At present, a variety of ICA algorithm has been proposed, in which the information maximization ICA blind source separation (Informax) algorithm is the most representative. Informax algorithm is that a suitable nonlinear function is introduced in the output, which makes the output information entropy

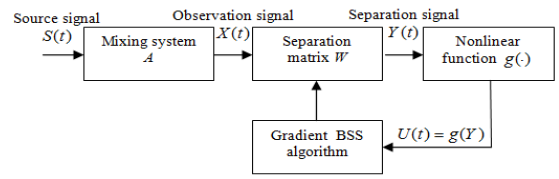

Fig. 2: Principle frame diagram of the Informax algorithm

to get maximization. (Yang, 2006) Informax algorithm principle frame diagram is shown as Fig. 2.

After the separation matrix W solution, each component yi of the output result Y is respectively used the nonlinear function $g_i(y_i)$ to processing, which makes the output total entropy $H(U) = H[g_1(y)) = H[g_1(y_1), ..., g_N(y_N)]$ achieve the maximum amount, if $g_i(y_i)$ is the accumulation of the distribution function for y_i, the algorithm is equivalent to the minimum mutual information (Feng *et al.*, 2008). The output total entropy amont is shown as formula (2):

$$H(U) = -\int p(U)\log(U)dU \quad (2)$$

Because:

$$p(U) = p(Y)/\prod_{i=1}^{N}\frac{\partial g_i}{\partial y_1} = p(Y)/\prod_{i=1}^{N} g_i^{'}(y_i) \quad (3)$$

$$H(U,W) = H(X) + \int p(Y)\log|W|\prod_{i=1}^{N} g_i^{'}(y_i)]dX \quad (4)$$

$H(X)$ is unconcerned with W, so we make the $H(U)$ is maximum should make:

$$\int p(Y)\log|W|\prod_{i=1}^{N} g_i^{'}(y_i)]dX$$

is maximum, also make:

$$E\{\log[|W|\prod_{i=1}^{N} P(y_i)]\}$$

is maximum under the PDF (probability densityfunction) of $p(X)$. The purpose of the self-adaptive processing is adjusting W and making the output total entropy quantity H(U, W) is the largest, U *is* not the output what we need, it just introducing auxiliary link to make each component of the Y possible independent. W adjust algorithm:

$$\Delta W = \mu\ [\partial H(U, W)]/\partial W$$

Among it, μ is study step length. And from the formual (4) we can see:

$$H(U,W) = H(X) + \log|W| + \sum_{i=1}^{N} E_X \log g_i^{'}(y_i) \quad (5)$$

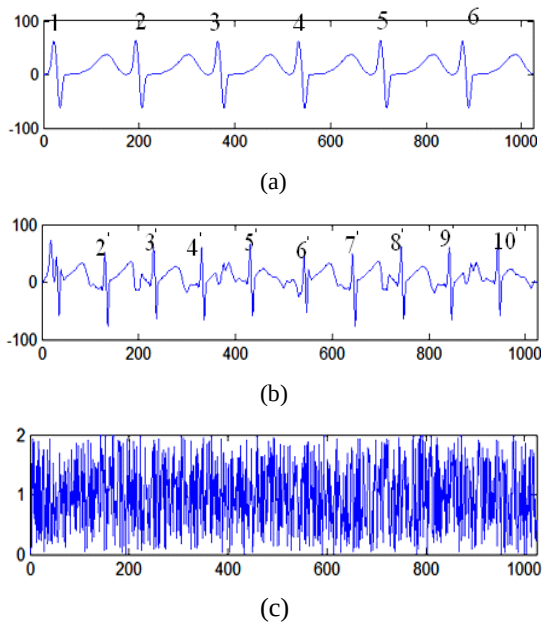

Fig. 3: Source signals

As the randomized gradient processing, instead the single sample value of the overall mean value, we can get:

$$H(U,W) = H(X) + \log|W| + \sum_{i=1}^{N} \log g_i^{'}(y_i) \tag{6}$$

Formual (6) derivation to W, $H(X)$ will be removed because of unconcerning with W:

$$\frac{\partial \log|W|}{\partial W} = W^{-T} \tag{7}$$

$$\frac{\partial \sum_{i=1}^{N} \log g_i^{'}(y_i)}{\partial w_{ij}} = \frac{1}{g_i^{'}(y_i)} \cdot \frac{\partial g_i^{'}(y_i)}{\partial w_{ij}} \tag{8}$$

Becuase:

$$\frac{g_i^{''}(y_i)}{g_i^{'}(y_i)} \cdot \frac{\partial y_i}{\partial w_{ij}} = \frac{g_i^{''}(y_i)}{g_i^{'}(y_i)} x_j \tag{9}$$

We can get:

$$\frac{\partial \sum_{i=1}^{N} \log g_i^{'}(y_i)}{\partial w_{ij}} = -\Phi(Y) X^T$$
$$\Phi(Y) = [-\frac{g_1^{''}(y_1)}{g_1^{'}(y_1)}, \ldots, -\frac{g_N^{''}(y_N)}{g_N^{'}(y_N)}] \tag{10}$$

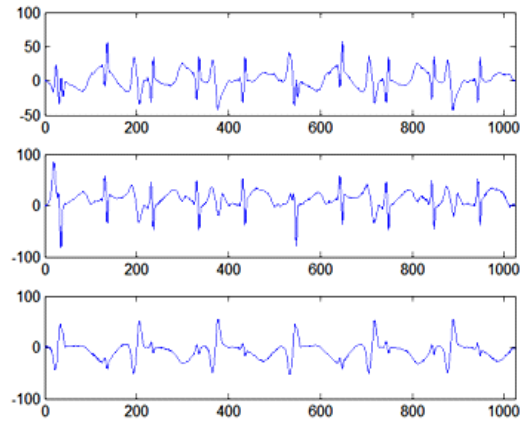

Fig. 4: Observation signals

In theory, $g_i^{'}(y_i)$ should take the PDF of the source signal. $g_i(y_i)$ is the cumulative probability distribution of $p(s_i)$. We can get formula (11) and (12):

$$\Delta W = \mu \frac{\partial H(U,W)}{\partial W} = W^{-T} - \Phi(Y) X^T \tag{11}$$

$$W(k+1) = W(k) + \mu_k [W^{-T}(k) - \Phi(Y(k) X^T(k))] \tag{12}$$

BSS SIMULATION

In order to validate the blind separation application of Informax algorithm this study presented in FECG field, we take two group of real ecg signal, respectively of maternal ecg signal and the fetal ecg signal and adding the noise signal, as shown in Figure 3. Among them, diagram (a) is the maternal ecg signal, diagram (b) is the fetal ecg signal, diagram (c) is the noise signal.

Through the 3*3 matrix blind mixing, the random mixed matrix A is shown as bellow:

$$A = \begin{bmatrix} 0.4447 & -0.5218 & 0.6057 \\ 0.6154 & 0.7382 & -0.9355 \\ -0.7919 & 0.1763 & 0.9169 \end{bmatrix}$$

After blind mixing, the mixed signal is shown as Fig. 4. The actual fetal ecg signal acquisition usually is the chaotic observation signal. If we take a nonlinear function y^3, step length is 0.002 and use Informax separation algorithm to separate the mixed signal. Before separation, the observation signal has carried out the mean and whiten processing.

From the Fig. 4 we can see, the blind mixing signals are hard to identify their initial condition. The results of using Informax BSS algorithm to separate observation signal are shown as Fig. 5. The separation results after using the Informax algorithm gained the better effect.

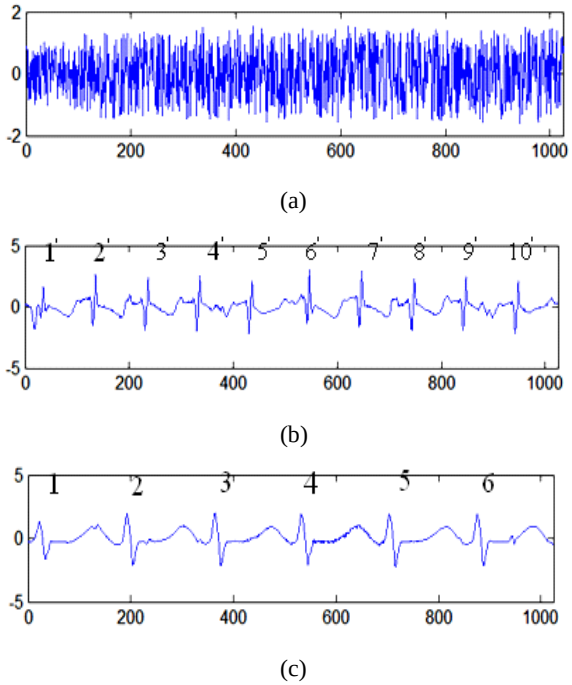

Fig. 5: Separation signals

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

Mothernal ECG value	Source signal (sampling point)	Separated signal (sampling point)	Error (%)
1	22	22	0
2	193	193	0
3	365	364	-0.27
4	534	532	-0.37
5	705	705	0
6	877	877	0

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

Fetal ECG value	Source signal (sampling point)	Separated signal (sampling point)	Error (%)
1'	18	18	0
2'	130	130	0
3'	231	230	-0.43
4'	331	331	0
5'	431	431	0
6'	542	542	0
7'	642	643	0.16
8'	743	742	-0.13
9'	843	843	0
10'	943	942	-0.11

In Fig. 5, diagram (a) is the the noise signal separated, diagram (b) is the fetal ecg signal and diagram (c) is the mothernal ecg signal. Through the comparison of the heart beating position between the ecg signal separated and the source signal, the separated signal can very accurately reflect the heart-beat moment of source signal. The comparison result of mothernal heart-beat position between the separated signal and source signal is

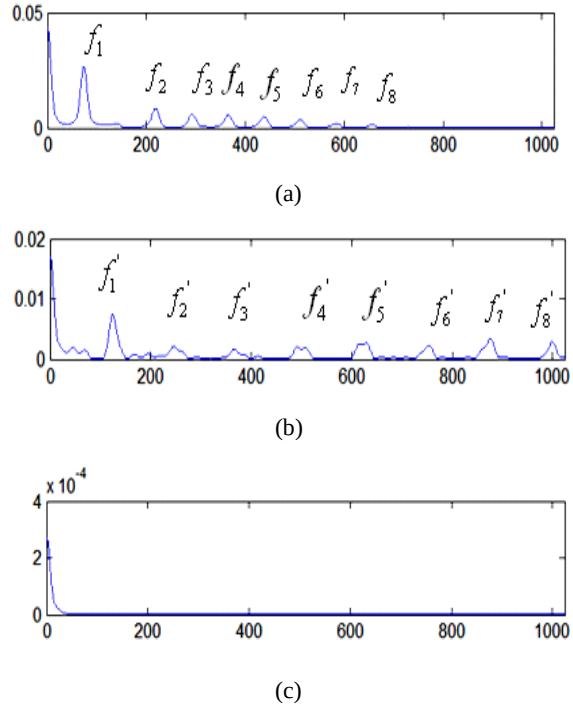

Fig. 6: Spectrum of source signal

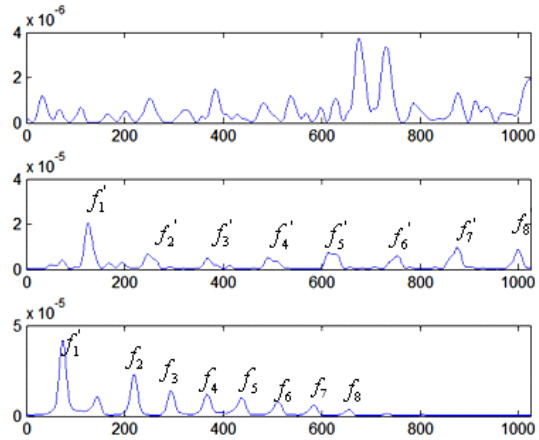

Fig. 7: Spectrum of separated signal

shown as Table 1. Mothernal heart-beat sample point position directly expressed in the digital from 1 to 6.

The fetal heart-beat position comparation between separated signal and source signal is shown as Table 2. Fetal heart-beat sampling point is expressed in digital from 1' to 10'.

Through the comparison we can see, signal separation effect is good and the absolute value of heart-beat time monitoring-error is less than 0.5%. In order to check the performance of separation algorithm this paper presented, we carried out the normalized spectral analysis to the separated signal. Source signal spectrum is shown as Fig. 6. Among the Fig. 6, diagram (a) is the mothernal

ecg signals spectrum, diagram (b) is the fetal ecg signal spectrum. Separated signal spectrum is shown as Fig. 7, diagram (b) is the fetal ecg signal separated spectrum diagram, diagram (c) is the mothernal ecg signal separated spectrum. Due to the blind signal separation has uncertain order, therefore, the separated signal and spectrum sequence are different with the source signals.

From the Fig. 6 and 7 we can see, the frequency characteristics between the separated mothernal ecg and fetal ecg signal is very similar to the source signal. In order to judge separation efficiency, we compared the frequency value between the separated signal spectrum and the source signal spectrum.

CONCLUSION

This study mainly discussed the nonlinear blind mixed ecg signals separation technology, introduced the model of the ICA algorithm and the implementation methods of information maximization (Informax) algorithm, studied the establishment of the objective function and the realization of the algorithm. Through the separation experiments of ECG blind mixed, we use the Informax algorithm to separate the mothernal and fetal ECG in higher precision, which proved this blind signal separation algorithm accuracy.

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