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Research and Simulation of FECG Signal Blind Separation Algorithm Based on Gradient Method

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Abstract: Independent Component Analysis (ICA) is a new developed signal separation and digital analysis technology in recent years. ICA has widely used because it does not need to know the signal prior information, which has became the hot spot in signal processing field research. In this study, we firstly introduce the principle, meaning and blind source separation algorithm based on the gradient. By using the traditional natural gradient algorithm and Equi-variant Adaptive Source Separation via Independent (EASI) blind separation algorithm, mixing ECG signals with noises had been separated effectively into the Maternal Electrocardiograph (MECG) signal, Fetal Electrocardiograph (FECG) signal and noise signal. The algorithm separation test showed that EASI algorithm can better separate the fetal ECG signal and because the gradient algorithm is a kind of online algorithm, which can be used for clinical fetal ECG signal of the real-time detection with important practical value and research significance.

Keywords: Blind signal separation, EASI algorithm, FECG, gradient algorithm, MECG

INTRODUCTION

FECG is an objective indicators reflecting the fetal heart activity, which can determine the fetal heart rate, judge whether the fetal is in distress, multiple births, function parameter analysis of heart and to prevent the neonatal disease (Li *et al.*, 2002). At present, the FECG acquisition method basically have two kinds, the fetal scalp electrode and maternal abdominal skin electrode. Fetal scalp electrode method will not only damage to the fetal and cannot be used in pregnancy. Maternal abdominal skin electrode has the advantage of its convenient, noninvasive and can be used in pregnancy, so, the medical workers and pregnant women have the deeply welcome (Ahmadi *et al.*, 2008). Because FECG signal is very weak and mixed with strong background noise, such as MECG (Zhenwei and Changshui, 2007), power frequency interference and baseline drift and so on, FECG accurate extraction and analysis is more difficult. So, looking for a effective signal separation method of FECG has important theoretical significance and clinical application value.

ICA is a recently developed new signal separation technology (Yang *et al.*, 2011), which is first proposed by Jutten and Herault (1991) the H-J algorithm is put forward based on the neural network technology. Jutten and Herault (1991) In 1994, Common first put forward the ICA concept (Comon, 1994), the basic ideas is isolated the original signal form the multiple source signal linear mixed. Besides assumptions source signal is independent of the statistics, without any other prior knowledge. ICA is developed with blind signal separation problem, so it is also known as the Blind Source Separation (BSS). ICA technology has developed and applicated in the fields of communications, image processing, physiological medical signal processing, speech signal processing, feature extraction, etc., Cichocki and Amari (2002) and Barros and Cichocki (2001). Among the BSS algorithm, the gradient algorithm is a kind of classic unconstrained optimization algorithm, the principle is simple, easy to realize, with equi-variant characters, which can realize the online calculation and has been widely used in BSS. Wen and Chen (2012) This study mainly introduced the EASI algorithm based on the gradient model and through the FECG separation simulation experiment, we can accurately get the FECG from the blind mixed signals.

METHODOLOGY

Minimum mutual information criterion: If we suggest *m* numbers of source signal and sensor, there is a basic relations between the measurement signal and source signal, which is shown as formula (1). Li and Zhang (2006):

$$x(t) = AS(t)+n(t) \quad (1)$$

The observation signal is X(t):

$$X(t) = [x_1(t), x_2(t),\ldots, x_m(t)]^T \quad (2)$$

X (t) is instantaneous linear mixed signal by the n numbers of source signal of $S(t) = [S_1(t), S_2(t), \ldots, S_n(t)]^T$, S(t) is source signal matrix and i = 1, 2, ..., n, which is n

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numbers of mutually independent random signals. Mixing matrix A = a and i = 1, 2, ..., m, j = 1, 2, ..., n.

In formula (1), $n(t)$ is noise jamming signal mixing in the source signal, source signal separation problem is to estimate the system matrix W, which makes the Y (t) passing through the X (t) is the estimation value of the source signal. That is the formula (3) as bellow:

$$Y(t) = WX(t) \approx S(t) \tag{3}$$

The Minimum Mutual Information (MMI) (Wu and Yan, 2011) is to find a accurate neural network weight value of matrix W, which makes each component of output Y(t) to have the minimize dependencies, even to zero and achieves the purpose of separation in true. We can use entropy to express the dependencies between signals. The dependence is expressed by the Kullback-Leibler degree between the joint probability density function $p(Y, W)$ and the product of the edge probability density function $\prod_{i=1}^{n} p(y_i)$:

$$I(W) = \int p(Y,W) \log \frac{p(Y,W)}{\prod_{i=1}^{n} p(y_i)} dy_1 \ldots dy_n \tag{4}$$

Among the formula (4), duet to the characters of the Kullback-Leibler degree, mutual information is nonnegative, it is that, I(W) $\geq$0. When and only when each components is mutual independence, the mutual information of Y(t) is equal to zero. That is $p(Y,W) = \prod_{i=1}^{n} p_i(y_i)$.

I (W) takes the minimal when the component of Y(t) independence each other. This is suitable for the measurement of independence information. For the estimates signal Y(t) to the blind separation problem, the mutual information is as formula (5):

$$I(W) = \int p(Y,W) \log \frac{p(Y,W)}{\prod_{i=1}^{n} p(y_i)} dy$$

$$= \int p(Y,W) \log p(Y,W) dy - \sum_{i=1}^{n} \int p(y_i) \log p(y_i) dy_i \tag{5}$$

According to the differential entropy value definition of the continuous random variable:

$$H(x) = -\int p(x) \log p(x) dx \tag{6}$$

We can get the formula (7) between input signal and output signal entropy by y = Wx:

$$H(y) = H(x) + \log |W| \tag{7}$$

Therefore, we can express the formula (5) as the mutual information entropy, which is shown as formula (8):

$$I(W) = -H(Y;W) + \sum_{i=1}^{n} H(y_i;W) \tag{8}$$

The mutual information I(W)$\geq$0 and Pierrie Common proved the mutual information amont isa comparison function of ICA. That is I(W) = 0, if W = ΛPA^{-1}. When the every component of Y(t) = WX(t) = ΛPA^{-1} X(t) is independent, I(W) equals to zero. And Y(t) = WX(t) = ΛPS (t) $\approx$ S(t) , here, Λ is any reversible diagonal matrix, P is any substitution matrix.

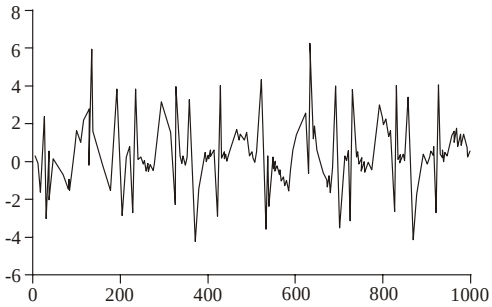
Bss algorithm based on gradient method: Because the blind separation problem is complex and having no universal analysis solution, in near ten years, researchers had done some simple hypothesis and put forward many good approximation solution based on the source signal's statistical properties. The existing gradient separation algorithm include the improvement Infomax algorithm, natural gradient algorithm, equi-variant adaptive source separation via independent algorithm and inverse iteration algorithm, etc.

Bell and Sejnowski (1995) put forward a kind of single feed forward neural network algorithm. Its characteristic is mixed by the W solution, the each component y_i of output y respectively uses a reversible drab nonlinear function $g(y_i)$ to treated and after giving an appropriate $g(y_i)$, through adjusting the W to make comprehensive information entropy $H(g(y))$ of $g(y)$ largest. Using the random gradient descent optimization algorithm and adopting the instantaneous or random gradient instead of the real gradient, the randomized gradient algorithm can be gotten as formula (9):

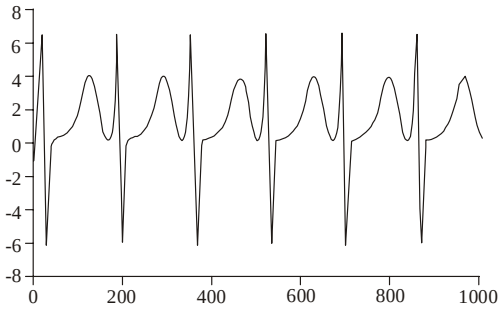
$$\Delta W = \mu[W^{-T} - g(y)x^T] \tag{9}$$

Among formula, μ is step length, g(y) is given nonlinear function, g(y) is each component of vector y executing given scalar function g(y). Infomax algorithm can effectively separate more super gaussian source signal. The disadvantage of this algorithm is that the convergence speed is slow and involves the inverse of the separation matrix W, once the condition number of W becomes poor, the algorithm can expand. If right multiplication W^TW of the randomized gradient, we can get the natural gradient, the natural gradient algorithm is shown as formula (10).

$$\Delta W = \mu[I - g(y)y^T]W \tag{10}$$



(a) Mixing observation source signal



(b) MECG signal

Fig. 1: Source signal

The natural gradient algorithm can't guarantee orthogonality of separating matrix *W* in iterative processes, Cardoso, etc put forward a kind of the equal changing adaptive independent separation algorithm. The main characteristic of EASI algorithm is to use relative gradient instead of randomized gradient and mix the numeral algorithm and separation algorithm together, which decomposes the separation matrix *W* into the product of orthogonal matrix and albino matrix. EASI algorithm is shown as formula (11):

$$\Delta W = \mu[I - yy^T - g(y)y^T + yg(y)^T]W \qquad (11)$$

Algorithm application in the FECG separation: In order to prove the accuracy in separating the FECG, we obtain the actual measurement signal from the mother's belly, in the processing of signal collection, many noise such as work frequency interface, MECG, etc., will mix in, the mix observation signal is shown as Fig. 1a. MECG is shown as Fig. 1b.

BSS SIMULATION

We suggest the observation signal containing the fetal ECG, mothernal ECG and the noise signal, etc. The natural gradient algorithm and EASI algorithm were carried out the mixed signal BSS and the results by using natural gradient separation algorithm and EASI algorithm to separate the source signals are shown as Fig. 2.

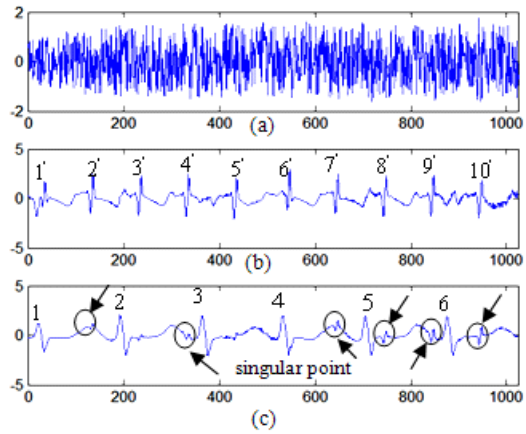


Fig. 2: Separation signals by using natural gradient algorithm

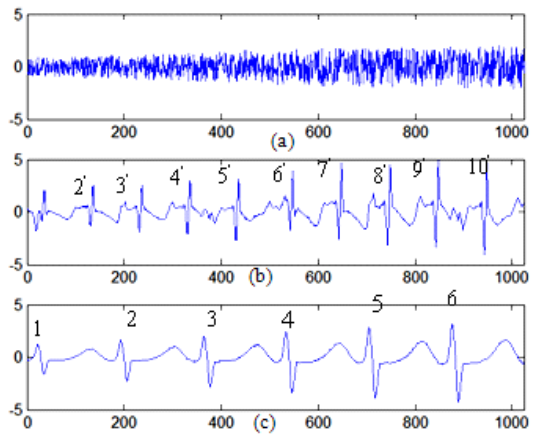


Fig. 3: Separation signals by using EASI algorithm

Figure 2 is the result by using the natural gradient algorithm, (a) is noise signal, (b) is FECG, (c) is MECG. The Arrow in Fig. 2 describes the singular point that can not be separated out of the MECG. From the separation result we can see, MECG still has FECG by using the natural gradient algorithm and we use circle to point out. From the Fig. 2b and c we can see, in separating the FECG from the mixing signal, part of noise can not be separated from the mixing source signal. Adopting EASI algorithm to separate the mixing source signal, the result is shown as Fig. 3.

Among the Fig. 3a is the noise signal, b is FECG and c is MECG. From the separation result we can see, we can completely separate the MECG, FECG and the noise signal by using EASI algorithm.

Comparing BSS algorithm: From the maternal ECG signals we can measure the position of each heart beating and we compare the natural algorithm and EASI algorithm, the results are shown as Table 1.

Table 1: Maternal heart-beat position compare between the separated signal and source signal

MECG value	Source signal (time)	Natural gradient algorithm (time)	EASI algorithm (time)
1	22	22	22
2	193	193	193
3	365	364	365
4	534	532	534
5	705	705	705
6	877	877	877

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

FECG value	Natural gradient (sampling point)	EASI algorithm (sampling point)
1′	18	18
2′	129	130
3′	229	230
4′	330	331
5′	431	431
6′	542	542
7′	642	643
8′	741	742
9′	843	843
10′	943	942

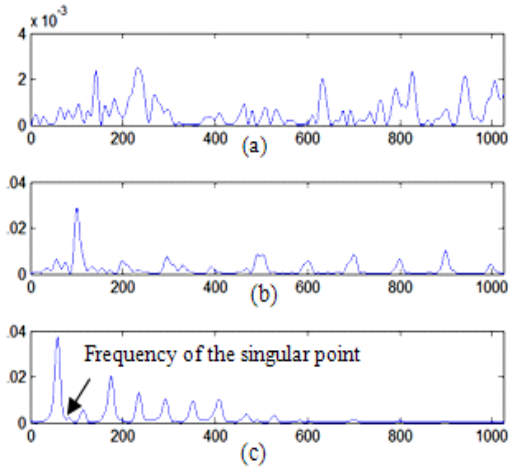


Fig. 4: Frequency spectrum by using the natural gradient algorithm

From the separation result, comparing the separation MECG by the natural algorithm and EASI algorithm with the actual MECG. The heart beating position of separation signal by using the natural gradient algorithm and EASI algorithm are shown as Table 2.

From Table 2 can see the FECG separation result is basic same and the two kinds of the separation algorithm verified the separation efficiency each other. The frequency energy diagram in natural gradient separation algorithm, which is shown as Fig. 4.

In Fig. 4a is the frequency spectrum of the noise signal, b is the frequency spectrum of the FECG, c is the frequency spectrum of the MECG. We can find the singular frequency point in the MECG. The frequency energy diagram in EASI separation algorithm is shown as Fig. 5.

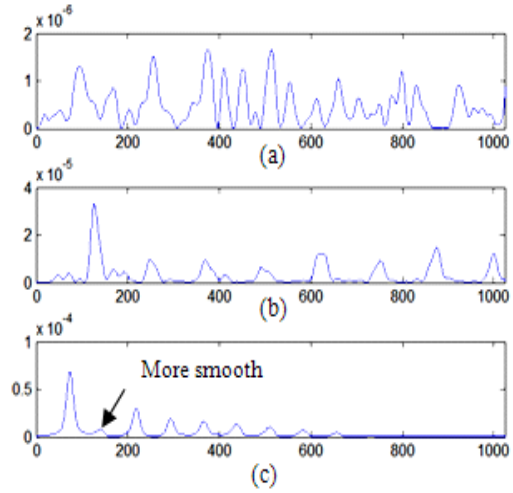


Fig. 5: Frequency spectrum by using the EASI algorithm

In Fig. 5a is the frequency spectrum of the noise signal, b is the frequency spectrum of the FECG, c is the frequency spectrum of the MECG. From the Fig. 5 we can see, the singular frequency point is not obviously in the Fig. 4c, which is more smooth and proves that the fetal ECG can not be separated by the natural gradient algorithm. And the experiment results proves the EASI algorithm can separate the mixed signal better than the natural gradient algorithm.

CONCLUSION

This study detailed study the bind signal separation algorithm, through using the natural gradient algorithm and EASI algorithm, we can get FECG from the blind mixed ECG. The simulation result realizes the mixed signal separation effectively. In addition, through comparing the two algorithm, we can find the EASI algorithm is better than the natural gradient algorithm. The gradient algorithm can realize online blind separation, which can be applied to the clinical fetal disease monitoring and online protection.

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