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Research of Blind Mixed Signal Separation Technology Based on Fixed Step Size Natural Gradient Algorithm

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Abstract: This study carried out the blind signal separation experiment based on the natural gradient algorithm for the blind mixed square wave, sine wave, amplitude modulation wave and noise signal, etc. The simulation verified that the natural gradient blind signal separation algorithm can accurate complete mixed signal separation and analysis thorouth simulating the complex random mixed source signal. Compared the blind signal separation performance of natural gradient algorithm in different step size condition. It is concluded that the selection of the step size is important to the steady-state error and the convergence speed. This study analyzed the convergence speed and the steady performance of the algorithm under the condition of fixed step size 0.005 and 0.1.

Key words: Blind signal separation, blind mixed signal, natural gradient algorithm, steady performance, convergence speed

INTRODUCTION

Blind signal separation technology (Ma *et al*., 2006) is the source signal is unknown and under the unknown blind mixed process condition, separate out the initial source signal from the blind mixed signal. In the field of signal processing, blind source separation technology has become a greatly challenging research hot spot which attracted many experts and scholars at home and abroad to study the blind source separation problem. 'Cocktail' issue first caused people to the further research in the blind source separation problem. (Choi and Cichocki, 1997) In a many people at the same time to talk with some other environment noise, who to separate the need voice signal from the received signal indeed by the detector, that is the problem of blind source separation. (Bronkhorst, 2000) Generally, blind source separation problem of the basic ICA model can be divided into: Linear instantaneous mixing, linear convolution and nonlinear mix. (Yang and Hong, 2006) This study mainly studied the instantaneous mixed linear model. Blind source separation method mostly is an unsupervised learning method and it must construct an appropriate objective function according to some theory and then carries on the optimization to solve it. After determining the objective function, the need solution mixing matrix can be calculated through the appropriate optimization algorithm. In this study, we study a fixed step size natural gradient algorithm in blind mixed models of different types of signal analysis and applications and research the role of step size in the algorithm performance.

BLIND SEPARATION MODEL

Figure 1 is the ICA blind source separation model diagram (Shi, 2008), in the figure, $S_1(t)$, $S_2(t)$, ..., $S_n(t)$ is the unknown source signals, the blind mixing system A is the signal transmission channel, N is the noise, the $x_1(t)$, $x(t)$, ..., $x_m(t)$ is the observation mixed signal, W is the separation system needed to solve, by separating system we can well get the best estimate unknown source signals, $y_1(t)$, $y_2(t)$, ..., $y_n(t)$ is a demanding best estimate source signal.

From the presence of noise signal or not it can be divided into having noise model and having no noise model. Because of there being noise model, linear convolution mixing and nonlinear mixing model, etc, among them, the blind mixing mode of having noise signal and some nonlinear system is complex, therefore, this paper choosed an instantaneous mixed linear model as the research object.

The mathematical expression formula to the ICA blind signal separation basic model is shown as below:

$$x = A \bullet s, y = w \bullet x \tag{1}$$

In equation 1, s expresses a group of nnumbers independent source signals. $S = [s_1(t), s_2(t), \ldots, s_n(t), \ldots, s_n(t)]^T$ passed through teh unknown transmission channel A, receiving observation signal $x = [x_1(t), x_2(t), \ldots, x_m(t)]^T$ and tatal having m numbers observation signal, supposing $m \geq n$ and simple into $m = n$. In equation (1),

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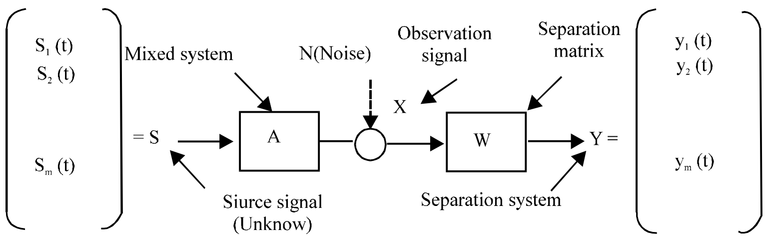

Fig. 1: ICA blind signal separation model

is a matrix consisted by n numbers independent source signal, A is an unknow m×n mixing matrix which is closely related to the mixed system model. (Hyvarinen and Karhunen, 2007).

Equation (1), x is observation mixing signal matrix, W is calculation m×m solving mixing matrix, Y is the estimates of source signal obtained by the ICA method. So, the key of using ICA method for blind source separation is how to solve a solution mixed matrix W.

ICA basic solving process. ICA basic solving process mainly includes three steps:

- Pretreatment
- Establish the objective function
- Select optimization algorithm

The selection of the objective function determines the consistency and robustness of the ICA. The selection of the objective function is related to the convergence speed, requirements and the computer's memory.

Common objective function ways are: The high order cumulant, negative entropy, mutual information and maximum likelihood estimation. The paper's program design is based on the maximum likelihood estimation to select the objective function. For ICA solving problem, after selecting the appropriate objective function, the next step is to select the appropriate optimization algorithm to learn which making the selected objective function into the maximum or minimum and to get the right solution mixed matrix w, make the independent component isolated as much as possible is equal to the source signal. The optimization algorithm can be divided into many categories from the different method. In this study, the program design by using the maximum likelihood estimates to obtain the selection of the objective function. The study adopts the natural gradient optimization algorithm to complete the blind mixed signal separation.
Due to the Fast ICA algorithm can not realize online blind signal separation, we carry out the signal separation and analysis by using the gradient algorithm because of the need of online in real time. But the Fast ICA blind signal separation algorithm have its advantages such as prcess time is short and convergence speed is fast, etc. (Hyvarinen and Oja, 1997).

ALGORITHM ANALYSIS

Informax algorithm is a commonly used method to seek the extremum of the objective function L (W). Its main principle is: Firstly, selecting an initial solution mixed matrix and brought it into the objective function gradient L(W) in W(0) point, then in the negative gradient direction adding a new separation matrix to suit step size calculated form W(1) and then repeating the process. So the solving W of Informax algorithm is shown as equation 2:

$$\Delta W = u(k)\frac{\partial L(W)}{\partial W}\Big|_{W=W(k)} \qquad (2)$$

Among the equation 2, k is the number of iteration, u(k) is learning step size, without considering the number of k, the equation can be expressed as:

$$\Delta W = u(k)\frac{\partial L(W)}{\partial W}$$

Equation 2 is a kind of usual gradient descent method iteration formula. When selecting different object function L(W), we can get different iteration equation. This study adopted the maximum likelihood estimation as the object function calculation. We can ge the estimate equation Y = Wx when using the maximum likelihood estimation:

$$L_{ML} = \frac{1}{T}\sum_{i=1}^{T}\{\log(p_s(Wx))\} + \log|\det W| \qquad (3)$$

We can get the equation 4:

$$L_{ML} = E\{\log(p_s(Wx))\} = \int p_s(x)\log(p_s(y))dx + \log|\det W| \qquad (4)$$

If we carry out the derivation to the Eq. 4. We can get the equation 5:

$$\frac{\partial L_{ML}(W)}{\partial W} = W^{-T} - E\{\varphi(y)x^T\} \quad (5)$$

We can get the iterative formula of solving the mixed matrix W through substitute into Formula 5 to 2:

$$\Delta W = u(k)[W^{-T}(k) - E\{\varphi(y)x^T\}] \quad (6)$$

This is offline batch iterative formula of the Informax algorithm, if alternative the expectations with instantaneous value, we can get the online adaptive iterative equation of Informax algorithm:

$$\Delta W = u(k)[W^{-T}(k) - \varphi(y)x^T] \quad (7)$$

When selecting different objective function L(W), we can get a different iterative equation. Here, u(k) is the step size, g (·) is a closely related to the function to the source signal probability density function. Normally, for sub-gaussian signal, $g(\cdot) = y^3$ and for super gaussian signal, $g(\cdot) = \tanh(y)$. (Hyvarinen and Oja, 1997).

Infomax algorithm can effectively separate the multiple super gaussian distribution source signal. However, the main drawback of this algorithm are: slow convergence speed and because of needing the separation matrix inversion, once the condition of W in updating process, algorithm could have divergence. On this issue, Amari proposed the natural gradient algorithm based on the Riemannian space (Riemann). To discussing the ICA in matrix space, the natural gradient algorithm has the relation with the Informax algorithm:

$$\frac{\partial L(W)}{\partial W_N} = \frac{\partial L(W)}{\partial W_I} W^T W \quad (8)$$

After the analysis, we use instantaneous value $\varphi(y)$ y^T instead of the expected value $E\{\varphi(y)x^T\}$, the natural gradient algorithm can be represented as:

$$\Delta W = u(k)[I - \varphi(y)y^T]W(k) \quad (9)$$

Compared with Informax algorithm, the natural gradient algorithm can avoid the matrix inversion, the actual calculation number is decreased obviously and also accelerates the convergence speed. Through the practice has proved that the natural gradient algorithm is a learning algorithm which has a very good separation effect, at the same time, the algorithm does not require the observation signal bleaching processing, so that the signal processing steps can be simplify which has become a very common learning algorithm.

In this article, we adopted the the independence of crosstalk error in the global transfer matrix elements to measure the pros and cons of the separation performance. The crosstalk error is presented by the Amari first which expressed the separation matrix W inverse matrix and the degree of deviation of mixed matrix A. The crosstalk error is defined as equation 10:

$$E = \sum_{i=1}^{N}\{(\sum_{i=1}^{N}\frac{|g_{ik}|}{\max_j |g_{ij}|} - 1) + (\sum_{k=1}^{N}\frac{|g_{ki}|}{\max_j |g_{ji}|} - 1)\} \quad (10)$$

Among the equation (10), g_{ij} expresses the elements of global transfer matrix G = WA. E is a number of not less than zero, only when the signal is completely separated, E = 0. In the practice, when the algorithm convergence, the crosstalk error is a very small value. (Amari *et al*., 1996)

SIMULATION EXPERIMENT

Assuming the initial signal is consist of the square wave signal, sine wave signal, amplitude modulated wave signal and noise signal which is respectively shown as Fig. 2 and the sampling frequency is 1 MHz.

We analyze and calculation them by sampling the numbers of 4000 points, after the random matrix blind after mixing, the observation waveforms can hardly be identified which is respectively shown as Fig. 3.

On carrying the blind signal separation to the collected observation we adopt the natural gradient blind

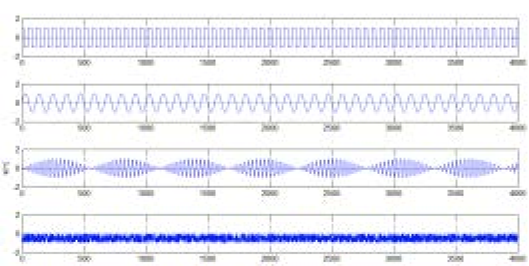

Fig. 2: Initial signal waveform

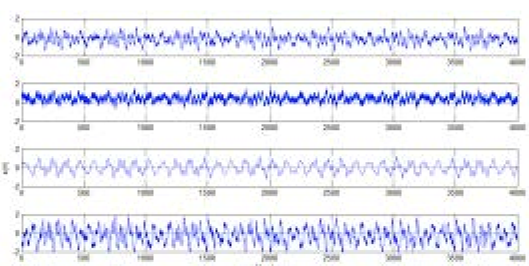

Fig. 3: Blind mixing signal waveform

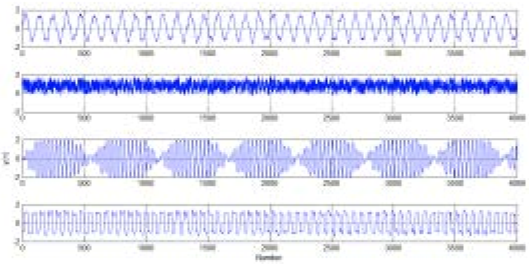

Fig. 4: Separation waveform

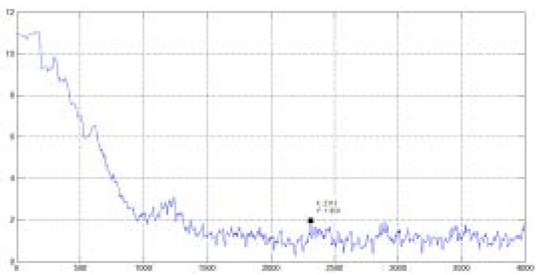

Fig. 5: Crosstalk error (step size u = 0.005)

separation algorithm to complete the blind mixed signal separation practice in the initial step size u = 0.005. And the nonlinear function is y^3. The waveform of separation results is respectively shown as Fig. 4.

From the Fig. 4 we can see, this algorithm paper research can accurate separate the blind mixed signal, the crosstalk error is shown as Fig. 5.

From the crosstalk error Fig. 5 we can see, the algorithm can realize convergence in the iteration of 1200 times and the maximum crosstalk error in the steady state is 1.959. In order to study the step size's effect to the separation performance, we study the natural gradient blind source separation algorithm by using the step size of 0.01. The algorithm can also achieve the signal blind source separation and the crosstalk error is shown in Fig. 6.

From the Fig. 6 of the crosstalk error, when the step size is 0.01, the algorithm can realize convergence with the iterative times less than 1000 which namely that choosing a large step size, the algorithm convergence speed is faster but the steady state performance is poorer, from the Fig. 6 we can find, the maximum crosstalk error is 3.453 after the algorithm trends to steady state.

Thus, the gradient algorithm is sensitive to step size selection, the different separation result can be brought in the minute differences. Through the simulation test, we can get the result that the gradient algorithm in different step size selection is a key problem. In the future, we will

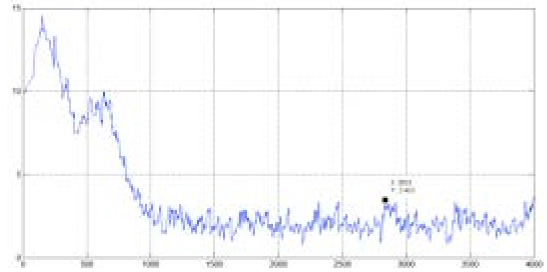

Fig. 6: Crosstalk error (step size u = 0.01)

study the step size adaptive natural gradient blind mixed signal separation technology.

CONCLUSIONS

This study introduced a kind of natural gradient algorithm to carry out the mixed blind signal separation. The simulation experiments show that the algorithm can effectively separate the blind mixed signal. The natural gradient algorithm has the equal changing character, such as the order and phase cannot be determined, on the other hand, due to the amount of calculation algorithm, the convergence speed and steady state performance is contradictory, so, we must carry on the comprehensive consideration on the selection of step size which is one of the research direction in the future.

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