Anti-jamming Technology of Frequency Hopping Communication based on Improved ICA-R

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Abstract. Aiming at the problem that the traditional frequency hopping communication in the complex electromagnetic environment is slightly less, this paper proposes applied the Blind Extraction technique in the Frequency Hopping communication. By this way, FH communication can keep the communication in the condition of the communication frequency band being interfered by interference signal. In allusion to the problem of the poor convergence rate, we regard inequality constraints of the operator in the Lagrangian function method as the restart condition of algorithm, which can improve the convergence rate of the algorithm.

1. Introduction

With the increasingly development of communication countermeasure techniques and technologies of electromagnetic war, FH communication is facing more and more complex environment and survival challenge. Only by improving high frequency hopping rate, increasing jump frequency band width efficiency measures to improve the anti-interference ability has achieved little in the increasingly complex electromagnetic environment [1]. In this article, blind extraction is introduced into the FH communication to improve the anti-jamming performance.

Blind Source Separation is widely used in speech[2], images[3], biomedical[4], earthquake[5] and other signal processing field. Literature [6] applied BSS in FH communication to improve anti-jamming performance. But in anti-interference application, we only need the source of the signal. BSS will separate all signal (jamming signal included) by default that can caused huge waste of the system in the process of decoding and storage. In addition, the sequence of separated signal is random, this means that system not only stores all of the signals but also needs specialized signal recognition from multichannel separate signals, which will be an additional burden in the system and adds unnecessary waste of resources. This article will apply Blind Extraction in anti-interference. In allusion to the low convergence rate of the ICA-R algorithm(one of Blind Extraction algorithm), this paper proposes to apply the improved ICA-R algorithm which can restart self to guarantee the robustness in the Frequency Hopping communication.

2. Modle

2.1 BLIND SOURCE SEPARATION.

Just rely on the non-Gauss, independence, non-stationary, sparse, and other statistical properties of received signal, BSS(Blind Source Separation) attempts to recover the various independent components of signals from the recorded signals without the source signal and the related parameters in the transmission channel. The so-called "Blind" refers to the lack of a priori information. In other words, BSS is the estimation process which estimates the source signal s(t) and mixed matrix A in the case of only know observation data x(t) =As(t). So BSS also called ICA (Independent Component Analysis).

The purpose of ICA is to reach a demixing matrix w which allows the separated signals to be statistically independent each other to inversely recover the original sources from the observations x(t), made the separation system output signal vector $y(t) = [y_1(t), y_2(t),..., y_m(t)]$ what is the estimated source vector, the demixing model is

$$y(t)=Wx(t)=WAs(t)$$

$s(t)=[s_1(t), s_2(t), \ldots,s_m(t)]$ is the original signal, $x(t)=[x_1(t), x_2(t), \ldots,x_n(t)]$ is the observed signals, and A is the a mixing matrix with size (N×M)(assuming that the observed signals are the linear mixtures of the original signals).

The ICA algorithm can be divided into two categories , one kind is iterative estimation method based on the rule of information theory and another kind is algebraic method based on statistical. But in principle, they are all using the independence and non-Gauss of source signal. About the method based on information theory research, scholars proposed a series of estimation algorithm from MMI(Minimum Mutual Information), maximum likelihood model, negentropy-maximization, etc. Such as Fast ICA [7], Infomax [8], Maximum likelihood estimation [9], etc.

Though scholars have researched the communication anti-jamming technology based on BSS, little literature have been referred. Several paper [6] [10] [11] proposed applying BSS in anti-interference. But they only proved the feasibility of blind separation in the field of anti - jamming, and did not propose feasible solutions for the specific application. This article gives an application of BSS in anti-interference. We apply Blind Extraction (an extension to BSS) in communication anti-jamming to Solve the problem of the storage and filtering of signal. In order to solve the problem of high failure rate of blind extraction, this article introduces a mechanism to restart algorithm and increases the robustness of the algorithm.

2.2 Constrained Independent Component Analysis

The literature[12] (Lu and Rajapakse，2005) firstly introduced a reference signal which converted from the priori information into the ICA algorithm, and turned BSS to optimization problem with constraints. This new algorithm called Reference Independent Component Analysis (ICA with Reference, ICA-R) or Constrained Independent Component Analysis (Constrained ICA, CICA). CICA has a wide range of applications in medical signal processing, computer processing, etc. The new framework is given by

$$\begin{aligned} \text{Min:} \quad & L(W) \\ \text{s.t.:} \quad & G(W) \leqslant 0 \\ & H(W)=0 \end{aligned}$$

L(W) is the objective function to measure the independence of signal. G(W) and H(W) reflect the known prior information and other additional conditions. Obviously, CICA changes the traditional ICA as a constrained optimization problem to increase the stability of convergence and save the identification process of target source signal.

We modify the Fast ICA (the traditional ICA algorithm) to the frame of the CICA. First, using the negative entropy to measure independence of signals:

$$J(Y)=H(Y_{gauss})-H(Y)$$

Y_{gauss} is a Gaussian random variables with the same variance of Y, H (.) is the differential entropy of a random variable. According to information theory, Gaussian random variables have the greatest differential entropy in random variables with the same variance. J(Y)=0 when Y obeys Gaussian distribution; the stronger non-Gaussian of Y, the smaller the differential entropy and the greater the value of J(Y). So J(Y) can be used as a measure of the non-Gauss property of the random variable Y. It is obviously impractical to know the probability density distribution function of Y, so we use the following approximate formula:

$$J_g(Y)=\{E[G(Y)]-E[G(Y_{gauss})]\}^2$$

E[.] is mean operation; G(.) as a nonlinear function, take G1 (Y) =tanh (a_1y) or G_2 (Y) =y^3,etc.

R is a reference signal relating to the source signal we interested in. We define a closeness measurement function ε(y,r) represents the distance from the source signal Y=WX we interested in to reference signal R and get the extreme values of ε(y,r).

$$\varepsilon(w^T x,r) \leqslant \varepsilon(w_1^T x,r) \leqslant \cdots \leqslant \varepsilon(w_{m-1}^T x,r)$$

This means that $y=w^Tx$ is the most close to the reference signal r than other estimate output of the independent component (IC) $y_i = w_i^Tx$, i=1,..., m-1. Define a function with inequality constraints:

$$g(w)= \varepsilon(w^Tx,r)-\xi$$

ξ is a threshold. Obviously, there is a suitable threshold ξ, to ensure that only the independent component w=w0 that most similar to component signal to set the following

$$g(w) \leqslant 0$$

Get the following the CICA framework:

$$\begin{aligned} \text{Max} \quad & J(y)\approx \rho\, [E\{G(y)-E\{G(v)\}\}] \\ \text{s.t.} \quad & g(w) \leqslant 0 \\ & h(w)=E(y2)-1=0 \end{aligned}$$

J(y) is a negative entropy contrast function in Fast ICA algorithm. The unequal constraint conditions g(w) limits the output signal to source signal associated with the reference signal R. Equality constraint conditions h (w) limits the output signal to unit amplitude.

In order to search the global optimal solution, we construct the extended Lagrange multiplier, which can be expressed as:

$$L(W,\mu,\lambda)=J(y)+\mu^TG(W)+0.5\gamma(||G(W)||^2+||h(W)||^2)+ \lambda^Th(w)$$

m and λ are non-negative Lagrange multiplier; γ is penalty constant; ||.|| is Euelidean norm and $0.5\gamma||.||2$ is to maintain the local convex function of the optimization problem, which makes the local Hessian matrix is positive definite.

For the learning of Lagrange operator, the method general use is gradient ascent method . We take the Newton learning algorithm to solve the calculation, get the approximate Newton learning algorithm is as follows:

$$w\leftarrow w- \eta\, Rxx\text{-}1L'/s(w)$$

$$s(w) \leftarrow \rho\, E\{G''(W)\}-0.5\, \mu\, E\{g''(w)\}- \lambda$$

The iterative algorithm of operator μ and λ based on the gradient is as follows:

$$\mu \leftarrow \max\{ \mu + \gamma\, g(w),0\}$$

$$\lambda \leftarrow \lambda + \lambda\, h(w)$$

2.3 Problems and analysis in application

Considering the complexity of the practical application environment, the mixed signal may contain multiple independent components. In addition to the signal we need to extract, there may be other independent components which close to the reference signal. These independent components can cause the Lagrange algorithm to converge or fail. The experimental results show that the blind extraction algorithm can extract the failure rate of 10%.

In the formula, the operator μ is a very explicit state indicator which is used to adjust the intensity of the constraint. When the solution is not in the feasible region, μ can be increased, but if the solution is in the feasible region, the operator is reduced down to 0(Inequality constraints invalid). In ICA-R algorithm, we use Newton-like learning algorithm to learn the extended Lagrange equation, which makes the weight vector w develop to the feasible region. In the process of operation, the μ and λ are used to constrain and guide the weight vector w. μ is the key to the algorithm which restrain solving signal to the reference signal. The increased operator represents the weight vector w offset the range of feasible solutions and smaller operator represents the weight vector w is in the scope of feasible solution. Since the solution is the beginning, there are many independent components in the data. The real feasible solution region is unknown, each column contains a certain amount of source signal data, so weight vector w random value at the beginning of the operation of the algorithm. In the settlement process, the weight vector w is introduced into the feasible region by the constraint operator.

The normal condition is that the initial vector w is just in the feasible region. The inequality constraint may not always be excited (μ identical to 0) and the algorithm is based on the space motion along the equality constraints. Alternatively, the initial vector w is not feasible, the inequality constraints are excited and guide the initial vector w to the feasible region iteratively. But there is a special case that the initial vector w is not directed to the feasible region, but the operator μ has changed to 0 (inequality constraint failure), then the initial vector w fell in another independent component region. At this time the operator will be restarted, but the initial vector w is not necessarily introduced into the feasible convergence region. The operator will lead w to the area of the other independent components and then re - off the operator. So the operator is started and failed, leading to the phenomenon of shock and false convergence.

2.4 Improved algorithm

This section presents stable and reliable ICA-R algorithm. The basic idea is that it is impossible to get the ideal inequality constraints in practice, but we can redesign a rule to avoid the error convergence problem of the original ICA-R algorithm. Specifically, our algorithm should include a mechanism that is able to check the possible error convergence phenomenon in the early iterations, and then restart the algorithm to set the initial value to a more reasonable position. A direct and feasible method for early detection of errors is to monitor the changes of the Lagrange operator μ. When the discovery of the second growth of the operator, we should judge the convergence of the algorithm in the future. Once the algorithm is restarted, the weight vector direction angle should be changed about 0.5 pi relative to the previous weight vector. The methods used are as follows:

$$w \leftarrow w - \sum c_j (w^T w_j) w_j$$

3. Computer simulation

The simulation randomly generates 4 signals with 15000 data length, and the first and two channels are the frequency hopping communication signals of different FH patterns. The specific parameters of the FH signal are set in the simulation: modulation mode is 2FSK, FH frequency set is {30, 55,…, 405} MHz, the starting point is 30MHz, the frequency point spacing is 25MHz, 16 frequency points, the hopping rate is 1000hop/s, the information rate is 1000bps, the sampling frequency is 1000MHz. Third and fourth way are comb like interference and PBNJ interference. The PBNJ interference signal is amplified by Gauss white noise by 10 order Butterworth filter which is occupied by the 200MHz~400MHz frequency band. The comb like interference is amplified by the 10 order Butterworth filter in the Gauss white noise with 12 interference bands. Frequency centers of Interference bands are respectively corresponding to each FH frequency band and the bandwidth of each jamming band is 20MHz. The mixed matrix A was randomly generated at each time of the experiment, and the 2000 Mento-Carlo experiment was done. Relative to Lu proposed algorithm, get the relevant parameters.

The following figure for the relevant data of one experiment.Fig.1 is four source signals interception, including two frequency signal. Fig.2 is four mixed source signals .It is unable to distinguish the signal with the information from time domain. Fig.3 is a FH signal spectrum. Fig.4 is the spectrum of signal subjected to interference. Can be seen from the spectrum, the FH communication signal is completely covered by the interference signal. At this time, if not to take anti - jamming measures, the communication system will not be able to carry out normal communication. Fig.5 is a signal after the successful separation and Fig.6 is a signal after the failed separation:

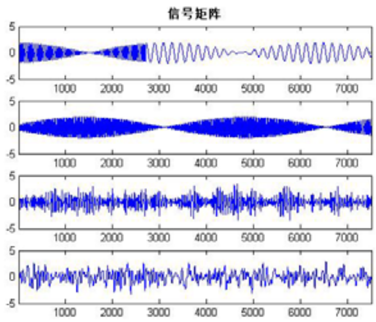

Fig. 1. Four source signal

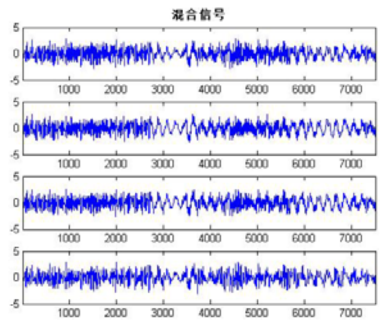

Fig. 2. Four mixed source signal

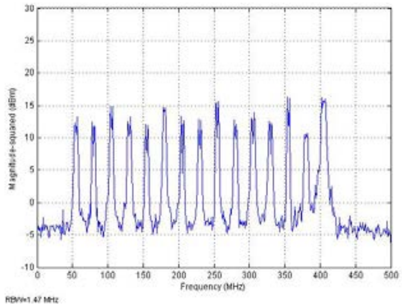

Fig. 3. Spectrum of Frequency Hopping signal

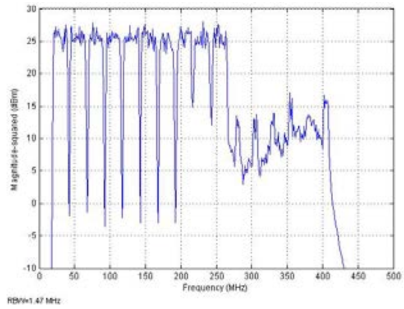

Fig. 4. Spectrum of disturbed signal

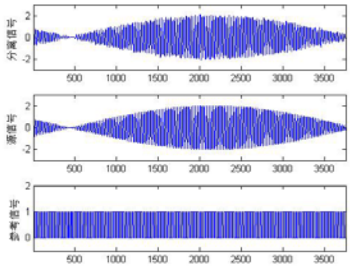

Fig. 5. Successfully extracted signal

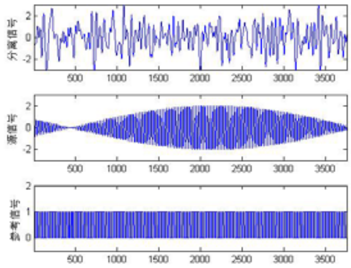

Fig. 6. Failed extract signal

After 2000 times Carlo-Mento experiment, compared with the Fast one-unit ICA-R Lu proposed, the results are as follows

TABLE I. EXPERIMENTAL RESULTS

Independent component	Component 1	Component 2
The failed number of original algorithm	224	215
The failed number of improved algorithm	0	0
Average CPU time of original algorithm	0.147539	0.095795
Average CPU time of improved algorithm	0.165351	0.115627

According to the above analysis, the improved algorithm has significantly improved compared to the original algorithm in the correct rate, reached 100%, which is due to the introduction of new algorithms error restart mechanism. By comparing the average CPU time of the algorithm, we can see that the improved algorithm is more than the original algorithm in CPU time. From table 1, the algorithm with the reset mechanism is Increased by 11% , which improves the robustness of the system.

The simulation of the BER simulation, fixed length data at 15000, 15dB SNR and SIR range of {-40dB , 0dB}, each letter to do simulation 2000 times. Fig.7 is simulation results. SIR is the energy of the signal and noise, as the measuring scale of the signal.

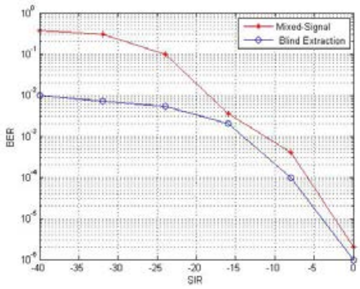

Fig. 7. SIR and BER

From Fig.7, we can see that the improved algorithm can effectively reduce the bit error rate, which has obvious anti jamming effect. When SIR is -16dB, the bit error rate of the interference signal and separated signals are both normal. However, when SIR is -24dB, the error rate of the interference signal is significantly affected by the number of 10^{-1}, and the bit error rate of separated signal can be kept small.

4. Summary

In this paper, the Blind Source Separation theory is applied in the FH communication to achieve signal separation under the condition of communication bandwidth covered by strong interference signal, which can greatly improve the anti-jamming ability of the FH communication system. Through the analysis and experiment of the blind source separation theory, a more suitable method for improving the blind extraction algorithm is proposed. The experiment proves that the improved algorithm has better robustness and is more suitable for FH communication.

References

[1]. A.M Zhang, S.J Liang, Z.Q Ma. Overview on Development of Military Anti-jamming Communication [J]. Communications Technology, 2011, 44(08):16-17.

[2]. Persia L D, Milone D, Rufiner H L, et al. Perceptual evaluation of blind source separation for robust speech recognition[J]. Signal Processing, 2008, 88(10):2578-2583.

[3]. Homayounzadeh A, Yazdi M, Shirazi M A M. Astrophysical Image Separation Using Independent Component Analysis[C]// Digital Image Processing, 2009 International Conference on. IEEE, 2009:275-278.

[4]. Hyvärinen A, Ramkumar P, Parkkonen L, et al. Independent component analysis of short-time Fourier transforms for spontaneous EEG/MEG analysis[J]. Neuroimage, 2010, 49(1):257-271.

[5]. Hazra B, Narasimhan S. Wavelet-based blind identification of the UCLA Factor building using ambient and earthquake responses[J]. Smart Materials & Structures, 2009, 19(2):328-335.

[6]. Y.H Wang, Modern Signal Processing Researchon Anti-Interference of Spread Spectrum Communication [D]. Zhejiang University, 2014.

[7]. A. Hyvärinen, Oja E. Independent component analysis: algorithms and applications.[J]. Neural Networks the Official Journal of the International Neural Network Society, 2000, 13(4-5):411-430.

[8]. Tian H, Jin J, Zhang C, et al. Informax-Based Data Fusion for Sensor Network[J]. IEEE Sensors Journal, 2009, 9(7):820-827.

[9]. Mayer A S, Huang C. Development and application of a coupled-process parameter inversion model based on the maximum likelihood estimation method[J]. Advances in Water Resources, 1999, 22(8):841-853.

[10]. Z.J Xin, A Semi-Blind Separation Algorithm for The Separation of Communication Signal and Interference Signal [J]. UESTC, 2013.

[11]. Y.C Zhao, Research on Independent Component Analysis Algorithm

[12]. and Its Applications to Signal Processing [D]. Shandong University, 2012.

[13]. Wei, Lu, Jagath C, Rajapakse. Approach and applications of constrained ICA.[J]. IEEE Transactions on Neural Networks, 2005, 16(1):203-212.