# Separation of Communication Signals Based on Underdetermined Blind Source Separation

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**Abstract.** The paper proposes an improved underdetermined blind source separation (UBSS) method of nonlinear mixture, which can be applied to the communication signals' separation during data link transmission in the complicated electromagnetic environment. The proposed method combines the advantages of wavelet analysis and kernel canonical correlation analysis (KCCA), and can enhance the signals' detection performance to the data link communication via separating the communication signals from the aliasing signals effectively. The simulation results show that the wavelet-KCCA BSS method can pick up the objective communicative signals even in low SNR condition, which has proper feasibility and effectiveness.

## 1. Introduction

With the development of networking and informationization, the status and role of data link communication is particularly prominent. And effective detection of communication signals during data link transmission is the precondition and basis of battlefield situational awareness [1], [2]. Due to the rapid development of the various wireless communication technologies and the exponential growth of the signal radiation source, the frequency band has become extraordinarily crowded. There are usually several or even dozens of different signals aliasing together within the same band width, which brings great difficulties to the signals' detection of the data link communication [3]. It has been a problem demanding prompt solution that how to separate the objective communication signals within complex electromagnetic environment while maintaining high stability and accuracy.

In recent years, blind source separation (BSS) methods have been used to solve the above problem [4]. But the traditional linear mixing algorithm does not consider the nonlinear factors in the actual process of signal transmission, which have a great influence on communication signals [5]. It assumes that communication signals in the reconnaissance receiver are simply linear superposition when the nonlinear mixing multiple signals are more common. Therefore, the traditional linear BSS technology is limited in practical application. At present, the nonlinear BSS method has made a certain progress, which is more similar to the reality. Nevertheless, most of the nonlinear method must satisfy the premise of determined or overdetermined condition. When the number of the sources is larger than that of the mixtures, the BSS problem is called an underdetermined BSS problem which the research is not yet mature [7], [8].

Contrapose the above problems existing in the signal detection to data link communication, an underdetermined blind source separation method of nonlinear mixture based on wavelet decomposition and kernel canonical correlation analysis (KCCA), which is named as Wavelet-BSS method, is proposed. The method combines the advantages of wavelet analysis and kernel canonical correlation analysis so that the signal detection performance to the data chain can be enhanced by separating the communication signals from the mixtures effectively. The result of the simulation shows that the method is practicable and effective.

## 2. Wavelet-KCCA Method

The major idea of the wavelet-KCCA method is to combine the advantages of wavelet analysis and kernel canonical correlation analysis, in which the wavelet analysis is used to solve the underdetermined problems while the KCCA is used to solve the nonlinear problems. So an underdetermined BSS method of nonlinear mixture can be converted into a linear determined problems that the theory is mature. The major process of the method is shown in Fig. 1.

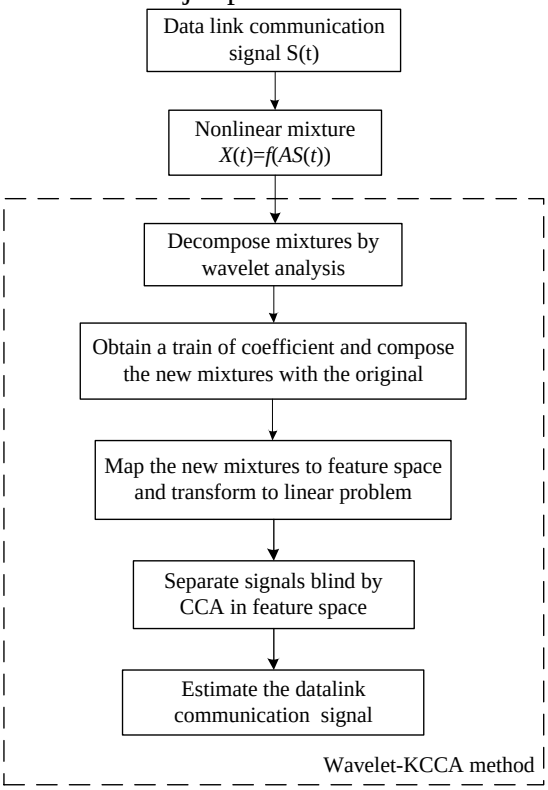



Fig. 1 The major process of the method

From Fig. 1, the proposed method can be divided into two parts:

1) the nonlinear mixture signals are decomposed to a series of approximate components with wavelet transform; these approximate components and original observation signals are combined to construct a new observation signal, and the underdetermined blind source separation problem is transformed to determined or overdetermined blind source separation problems.

For the given aliasing signal $x(t)$, we can obtain a train of coefficient using wavelet analysis. The high frequency part of the coefficient is the discrete minutiae coefficient $d_j(k)$ and the low frequency part is discrete approach coefficient $a_j(k)$. These two part have the following recurrence relation:

$$a_{j+1}(k) = \sum_{n=-\infty}^{\infty} a_j(n) h_0(n-2k) = a_j(k) * \overline{h}_0(2k) \tag{1}$$

$$d_{j+1}(k) = \sum_{n=-\infty}^{\infty} a_j(n) h_1(n-2k) = a_j(k) * \overline{h}_1(2k) \tag{2}$$

where $\overline{h}_k = h(-k)$, $h(k)$ is a weighting coefficient that is a discrete series. Assuming decomposing from $j$=0, $a_1(k)$ can be obtained from $a_0(k)$ after passing through the filter. And then, a train of approach coefficient $a_j(k)$ and $d_j(k)$ can be calculated by repeating the (1) and (2). Through the above way, decomposition coefficient $a_j(k)$ and original mixture signal $x(t)$ can be recombined into a new mixtures.

2) The new observation signal is mapped from low dimensional space to high dimensional kernel feature space; and the nonlinear blind source separation problem is transformed to linear blind source separation problem in the feature space. Then the canonical correlation analysis method is used to conduct blind source separation of the mixture signals, and the blind signal estimation is achieved.

It assumes that $y(t)=[y_1(t), y_2(t), \ldots, y_M(t)]^T$ is the new mixtures recombined by decomposition coefficient $a_j(k)$ and original mixture signal $x(t)$, where $M$ is the number of mixtures. The major idea of kernel method is mapping nonlinear mixture signals $y(t)$ from $R$ space to feature space F using nonlinear mapping, and mixtures are separated blind in $F$ space. Assuming the nonlinear function relationship is: $R \rightarrow F$ and $x \rightarrow \Phi(x)$, the new mixture signals in F space is:

$$\Phi(y(t)) = [\Phi(y_1(t)), \Phi(y_2(t)), \cdots, \Phi(y_M(t))]^T \tag{3}$$

In order to separating mixtures blind using canonical correlation analysis in F space, the linear combination of $\Phi(y(t))$ and $\Phi(y(t+1))$ must be obtained first ,which reaches the biggest self-correlation coefficient. The linear combination of $\Phi(y(t))$ and $\Phi(y(t+1))$ is given by

$$u = \alpha\Phi(y(t)) \tag{4}$$

$$v = \beta\Phi(y(t+1)) \tag{5}$$

where $\alpha$ and $\beta$ denote the required variable. The self-correlation coefficient of the linear combination is given as follows:

$$\rho = \frac{u^T \Phi \Psi^T v}{\sqrt{u^T \Phi \Phi^T v u^T \Psi \Psi^T v}} \tag{6}$$

where $\Phi = \Phi(y(t))$ and $\Psi = \Phi(y(t+1))$ .

The inner product is given by the sum of the kernel function in feature space as follows:

$$K_u = k(y_i(t), y_j(t)) = \Phi(y_i(t))^T \Phi(y_j(t)) \tag{7}$$

$$K_v = k(y_i(t+1), y_j(t+1)) = \Phi(y_i(t+1))^T \Phi(y_j(t+1)) \tag{8}$$

Equation (6) is given by kernel function as:

$$\rho = \frac{\alpha^T K_u K_v \beta}{\sqrt{\alpha^T K_u^2 \alpha \beta^T K_v^2 \beta}} \tag{9}$$

In order to maximizing the correlation coefficient ρ, (9) can be converted into (10).

$$\begin{aligned} &\max_{\alpha,\beta} = \alpha^T K_u K_v \beta \\ &s.t. \alpha^T K_u^2 \alpha = \beta^T K_v^2 \beta = 1 \end{aligned} \tag{10}$$

Equation (10) denotes a optimization problem and we can construct a Lagrangian function based on (10) as follows:

$$L(\alpha, \beta, \lambda_\alpha, \lambda_\beta) = \alpha^T K_u K_v \beta - \frac{\lambda_\alpha}{2}(\alpha^T K_u^2 \alpha - 1) - \frac{\lambda_\beta}{2}(\beta^T K_v^2 \beta - 1) \tag{11}$$

where $\lambda_\alpha$ and $\lambda_\beta$ denote the Lagrangian coefficient. Derivating $L$ by $\alpha$ and β respectively as follows:

$$\frac{\partial L}{\partial \alpha} = K_u K_v \beta - \lambda_\alpha K_u^2 \alpha = 0 \tag{12}$$

$$\frac{\partial L}{\partial \beta} = K_v K_u \alpha - \lambda_\beta K_v^2 \beta = 0 \tag{13}$$

Let $\lambda_\alpha = \lambda_\beta = \lambda$, and put it into (12) and (13) so that the optimization problem can be converted into a generalized eigenvalue problem as

$$\begin{bmatrix} 0 & K_u K_v \\ K_v K_u & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \lambda \begin{bmatrix} K_u^2 & 0 \\ 0 & K_v^2 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} \tag{14}$$

Canonical correlation variable $\alpha$ and $\beta$ can be obtained by calculating (14) when maximizing canonical correlation coefficient.

For KCCA-BSS method, the first group canonical correlation variable (CCV) gives the linear combination when maximizing the mixtures correlation. The second group CCV gives another linear combination when maximizing the mixtures correlation at the premise of uncorrelation with the 1st CCV and so on. $\alpha$ and$\beta$ given by (14) can be regarded as the separation matrix of the mixtures so that estimated communication signal s(t) can be obtained by multiplying $\Phi(y(t))$ by $\alpha$ or $\beta$.

The data link communication signals can be separating from several mixture signals by the above wavelet-KCCA method so that the signal detection performance of data link communication is enhanced.

## 3. Simulation And Analysis

If In order to demonstrate the effectiveness of wavelet-KCCA method in communication of data chain, two simulated signals as follows:

$$\begin{cases} s_1 = [1+\sin(20\pi t)]\cos(200\pi t) \\ s_2 = \sin(100t)+\sin(300t) \end{cases} \tag{15}$$

Setting the sampling frequency $f_s$=1000Hz, Fig. 2 shows the wave shape of the data link communication signal and Fig. 3 is the other source signal.

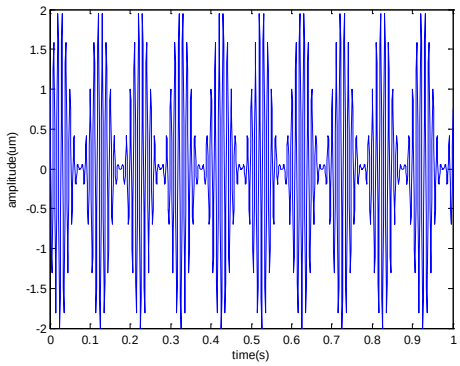



Figure 2.Wave shape of the data link communication signal.

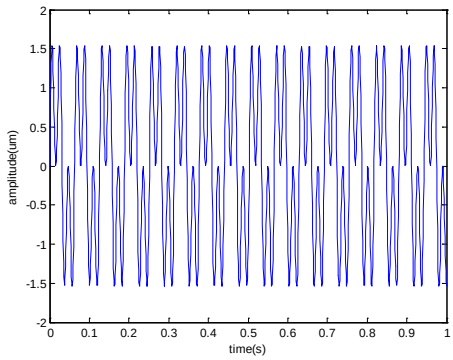



Figure 3. Wave shape of the other source signal.

In order to simulating the wireless channel, a 1×2 matrix $A$ and a nonlinear function that is exponential are generated randomly. Let the SNR be 20dB and the mixture signal can be obtained according to the Equation $x(t)=f(As(t))$. The time-domain mixture signal is shown in Fig. 4.

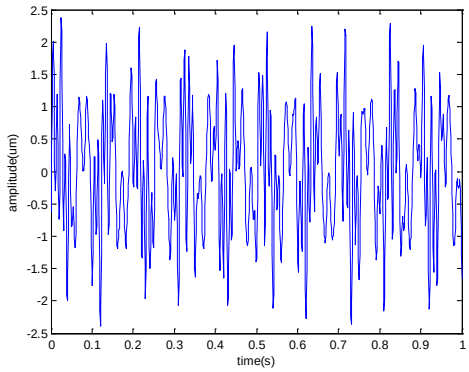
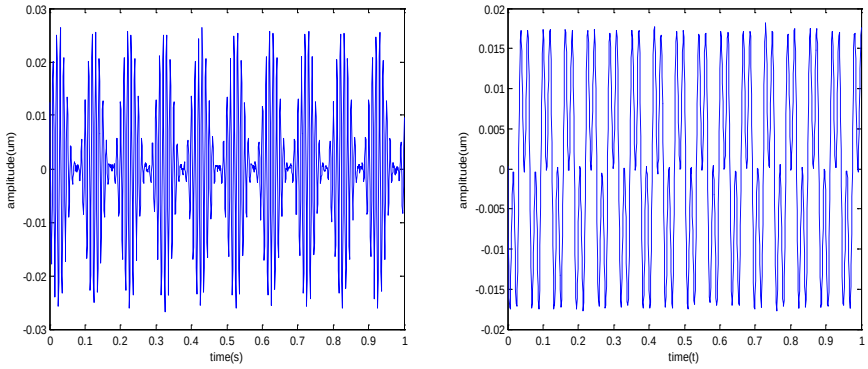



Figure 4. Wave shape of the time-domain mixture signal.

From the above setting, it is obvious that the simulation is a typical underdetermined BSS problem of nonlinear mixture. And we can utilize the wavelet-KCCA method to solve the problem. Fig. 5 (*a*)

illustrates separation results obtained about data link communication signal. Fig.5(*b*)shows the estimated wave shape of the other source signal.




(*a*) (*b*)

Figure 5. separation results of mixture signal.

As shown in Fig. 5, the recovered signals is very similar to the original sources except the amplitude and the initial phase so that the signal detection performance to data link communication is enhanced by using wavelet-KCCA method.

## 4. Conclusion

Research about enhancing the signal detection performance and accuracy to data link communication is vital. The paper combines the advantages of wavelet analysis and kernel canonical correlation analysis to propose the wavelet-KCCA method, and can enhance the signal detection performance to the data link communication via separating the communicative signals from mixtures. The proposed method transforms the underdetermined BSS problem to determined or overdetermined blind source separation problems by wavelet analysis firstly, and then nonlinear BSS problem is transformed to linear blind source separation problem by KCCA. Simulation illustrates this method is practicable and effective in separating the data link communication signals.

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