Advances in Engineering Research, volume 197
Proceedings of the 2020 9th International Conference on Applied Science, Engineering and Technology (ICASET 2020)

Blind Signal Separation of the Unknown Sources Number Based Under the Constraint of Space Direction

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ABSTRACT
The blind signal separation based on eigenvalue decomposition, and under the number of unknown sources, when the dimensionality of signal space is determined to be wrong, it will result in larger separation error. This paper uses the directional information of the array structure to build the blind signal separation algorithm based on the "Space kurtosis" spectrum, which can avoid the eigenvalue decomposition. The algorithm takes full use of the statistical independence of source signals and spatial distribution independence that can better separate the source signal and suppression noise. The simulation experiment results show the algorithm under the unknown source number that proposed in this paper features high accuracy and high robustness.
Keywords: *blind signal separation, uniform linear array, unknown source number, kurtosis.*

1. INTRODUCTION

In previously raised algorithm of blind signal separation, it can be divided in to two kinds of algorithms: the resource signal number needs to be known in advance and the resource signal number without having to be known in advance. The main representative for the algorithm of the resource signal number needs to be known in advance is the principal component analysis (PCA), which though solving the covariance matrix to find out the eigenvector corresponding to the large eigenvalue in the same number of the source signals. It utilizes Karhunen-Loeveb transformation to get the principal component vector that is to separate the source signal. However, in many application fields, the source signal number is unknown, so it needs to set reasonable threshold to the eigenvalue of the covariance matrix, and the eigenvalue number larger than the threshold is the number of the source signal. But especially in the case of low signal-to-noise ratio, as it’s hard to set reasonable threshold, the resulted separation signal error becomes greater. The BSS typical algorithm of the resource signal number without having to be known in advance is proposed by Amari[2] that uses the algorithm of blind signal separation with natural gradient as learning rule. It takes Kullback-Leibler divergence as the cost function, with good separability that can be applied in the blind source extraction for any number and is suitable for blind signal separation occasions of the unknown sources number[3]. But, Kullback-Leibler divergence needs to know the probability density distribution function of the source signal that is unknown in practical applications[4-6]. Therefore, in practical calculations, it must be replaced by a series of nonlinear functions[7]. In some special cases, these nonlinear functions can’t strictly match the real probability density distribution function of the original source signal, it results in the algorithm be converged to the error value.

As to increase the accuracy and robustness of the BSS in the case of unknown source signal number, this paper introduces the signal azimuth information into blind signal separation process, which uses kurtosis as the cost function to construct the "space - kurtosis" spectrum. It solves the separation weight vector through the large wave direction corresponding to the peak of the spectrum. On the assumption that the source signals are mutually independent, for the method of this paper, it doesn’t need to know the probability density distribution function of the source signal and the source signal number in advance. Besides, the natural gradient calculation hasn’t been used, so there’s no need to choose the learning step, making algorithm time-consuming and fixed and converge steadily to each separation weight vector. Because this algorithm uses more spatial information of the source signal than the previous blind signal separation algorithm, the simulation experiments show that the algorithm features high accuracy and high robustness.

2. DESCRIPTION OF BLIND SIGNAL SEPARATION PROBLEM UNDER SPATIAL DIRECTION CONSTRAINT

Blind signal separation separates the mixed signals received by the sensor array, and the mixed system can be described as below.

$$\mathbf{x}(\boldsymbol{k}) = \boldsymbol{A}\mathbf{s}(\boldsymbol{k}) + \mathbf{n}(\boldsymbol{k}) \tag{1}$$

Considering the sensor array is the uniform circular array, and the mixed signal has been restricted by the direction information. Therefore, the unknown mixed matrix is expressed as[8][9].

$$\boldsymbol{A} = [\boldsymbol{a}_1, \boldsymbol{a}_2, ..., \boldsymbol{a}_N]$$

In the formula, the i th column vector is

$$\boldsymbol{a}_i = [exp(-j2\pi f_c \tau_{1i}), exp(-j2\pi f_c \tau_{2i}), ..., exp(-j2\pi f_c \tau_{Mi})]^T \tag{2}$$

N is the number of the incident source signal; M is the array element number; $\tau_{ki} = \frac{r}{c}\cos(\frac{2\pi(k-1)}{M} - \theta_i)\cos\varphi_i$ is the i th signal's time delay relative to the array center On the element K; $\mathbf{n}(\boldsymbol{k})$ is the array element superposed noise; $r = c/2f_c$ is the radius of the array. Blind separation process is the use of observation signal $\boldsymbol{x}(\boldsymbol{k})$ to determine the separating matrix $\boldsymbol{W}$, making

$$\mathbf{y}(k) = \mathbf{W}\mathbf{x}(k) \tag{3}$$

$\mathbf{y}(k)$ is the estimation of $\mathbf{s}(k)$ source signal.

3. THE BSS BASED ON SPATIAL DIRECTION CONSTRAINTS

Under the constraint of uniform circular array, the spatial direction information has been introduced into the BSS.

3.1. Signal separation based on spatial direction information

When the direction of arrival (θ_i, φ_i) is known, we can use the minimum variance distortionless response (MVDR) to get the ith row phasor of the separating matrix W, which is.

$$\mathbf{w}_i = \frac{\mathbf{R}^{-1}\boldsymbol{a}(\theta_i, \varphi_i)}{\boldsymbol{a}^{\mathrm{H}}(\theta_i, \varphi_i)\mathbf{R}^{-1}\boldsymbol{a}(\theta_i, \varphi_i)} \tag{4}$$

$\mathbf{R}$ is the covariance matrix of the receipt signal $X(k)$.

3.2. DOA estimation based on the unknown source number of the kurtosis

In practical applications, the direction of arrival (θ_i, φ_i) in formula (4) is unknown, which should be estimated in advance. The kurtosis has been put forward by this paper as the cost function to construct the "space - kurtosis" spectrum. Here, suppose the unknown direction of arrival is (θ_i, φ_i), which uses MVDR to get corresponding separation weight vector as below:

$$\mathbf{w}(\theta, \varphi) = \frac{\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)}{\boldsymbol{a}^{\mathrm{H}}(\theta, \varphi)\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)} \tag{5}$$

Here, the signal corresponding to this direction of arrival can be separated from the mixed signal.

$$y(k) = \mathbf{w}(\theta, \varphi)\mathbf{x}(k) \tag{6}$$

The kurtosis of this signal is

$$P_\kappa(\theta, \varphi) = \frac{E[(|y(k)|)^4]}{E^2[(|y(k)|)^2]} - 3 \tag{7}$$

After plugging (5) and (6) into (7), the "space - kurtosis" spectrum can be defined as below:

$$P_\kappa(\theta, \varphi) = \frac{E\left[\left|\frac{\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)\mathbf{x}(k)}{\boldsymbol{a}^{\mathrm{H}}(\theta, \varphi)\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)}\right|^4\right]}{E^2\left[\left|\frac{\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)\mathbf{x}(k)}{\boldsymbol{a}^{\mathrm{H}}(\theta, \varphi)\mathbf{R}^{-1}\boldsymbol{a}(\theta, \varphi)}\right|^2\right]} - 3 \tag{8}$$

By changing (θ_i, φ_i) value, it can get the "space - kurtosis" spectrum whose peak is corresponding to the source signal's direction of arrival（(θ_1, φ_1) , (θ_2, φ_2) , …）. In the calculation process, the whole algorithm doesn't need to decompose the characteristics of the covariance matrix $\mathbf{R}$, so there's no need to estimate the source signal number.

Above BSS algorithm steps based on the spatial direction constraint is shown as below Figure 1.

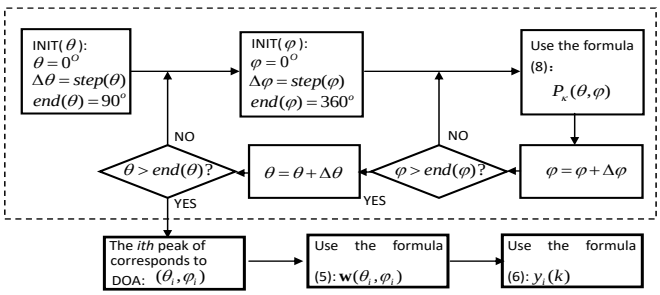


Figure 1 The flow chart of blind signal separation based on "space — kurtosis" spectrum

In the "space—kurtosis" spectrum, it may result in some false-spectrum peaks, there is no source signal existed in corresponding direction of arrival. Therefore, the signal separated from the false-spectrum peak is the noise. However, the existence of the false spectrum peak doesn't affect the accuracy of the signal separated by the real spectrum peak.

4. SIMULATION EXPERIMENT

Comparing the algorithm (Ku algorithm), AMUSE, ERICA, and SANG in this paper, to blindly separate the mixed signal x. For easy analysis and description of the experiment, this paper puts forward the algorithm named Ku algorithm.

For quantitatively analysing the blind separation effect of the mixed signals, the formula (9)is taken as the performance index (PI) for algorithm measurement.

$$PI = 1 - \frac{1}{N}\sum_{j=1}^{N}\max(\rho(y_i, s_j)) \tag{9}$$

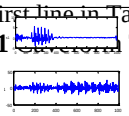
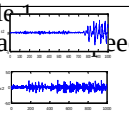
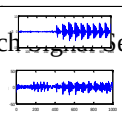
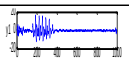
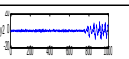
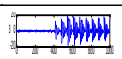
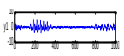
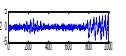
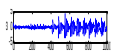
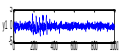
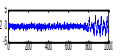
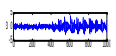
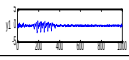
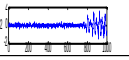
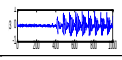
In the formula,

$$\rho(y_i, s_j) = \frac{|E\{y_i s_j\} - E\{y_i\}E\{s_j\}|}{\sqrt{E\{y_i - E\{y_i\}\}^2 * E\{s_j - E\{s_j\}\}^2}} \tag{10}$$

Experiment 1: Under SNR=10dB, separate the speech signal

Experiment condition: the number of array element is 12, and the source signal is s1, s2, and s3 which are incident from (50o, 10o), (150o,30o), (300o,60o) respectively. The incident signal is provided by Cichocki advanced brain signal processing laboratory, which has the bursty, shown as the first line in Table 1.

Table 1 Waveform Table of Speech Signal Separation

s1,s2,s3				
x1,x2,x3				
Ku				PI = 0.0112
AMUSE				PI = 0.4125
ERICA				PI = 0.2819
SANG				PI = 0.1446

From the PI value in Table 1, we can see that the separating property priority follows Ku, SNAG, ERICA, and AMUSE. From the view of the separated waveform, we can also find that Ku has been separated cleaner than the other three traditional methods, with small crosstalk. This is because that the Ku method has used the statistical independence characteristics of the spatial information and the signal.. SANG separation is also relatively clean, because the natural gradient descent algorithm can properly converge on the separate points of the separate signals. As original signals are independent of each other, when the SANG separation signals are independent of each other, these independent signals are the estimation of the source signals. But from the comparison of SANG's y1 and s1, it is seen that the phase is opposite to the source signal. This is because that SANG only considers the independence without considering channel characteristics. Therefore, the separated signals may be the signal phase different from the source signal phase. The cost function used by ERICA is the four-order cumulants of the signal, and the stable algorithm requires more cumulative sampling points. When each source signal separation outbursts, the algorithm's tracking performance for the signal will reduce, resulting in algorithm's convergence can't approach the pole, so there's the crosstalk. The component separated by AMUSE algorithm is better for noise suppression, but the crosstalk is more serious. For example, if y1 contains waveform of s1 and s2 components, which is because the AMUSE only uses the signal's second order statistics that can suppress the Gauss noise. But it can't suppress the crosstalk of other non-Gausses, it has serious crosstalk.

Experiment 2: The influence of noise on speech signal separation

The experimental conditions is as experiment one. The signal-to-noise ratio (SNR) changes from-10dB~25dB, the step noise change is 5dB and the noise impacts on each array elements. On every noise value, it conducts 200 Monte-Carlo experiments and calculates the PI value.Taking SNR as the abscissa and PI as the ordinate, the performance function diagram of each algorithm can be drawn as shown in Figure 2. Figure 2, when -10dB is used, the PI values of Ku and SANG algorithms are less than 0.5, and the AMUSE and ERICA are all higher than 0.5. It indicates that in the case of low signal-to-noise, the performances of AMUSE based on the second order statistics and the ERICA are low. When the noise-signal ratio is 0dB, the Ku algorithm will be able to separate the signal well, while the PI values of other algorithms are over 0.2.

Under all experimental noise conditions, the Ku method is better than the performance of SANG and ERICA for over 0.1 PI value; Ku is better than the the performance of AMUSE for nearly over 0.2 PI value. Therefore, the Ku algorithm proposed in this paper has better robustness to the SNR than the other three algorithms.

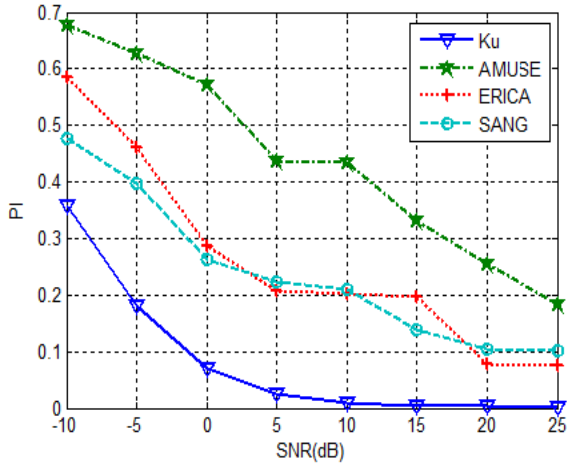


Figure 2 The influence of noise on the speech signal separation

5. CONCLUSION

This paper takes kurtosis as the cost function that separates the blind signal based on the "space — kurtosis" spectrum. Under the constraint of uniform linear array, it should first obtain the kurtosis of the separation signal of the whole array flow pattern, and get the peak of the "space kurtosis" spectrum. Through searching the direction of arrival of the source signal obtained by the spectrum peak, it then uses the separation weight vector of the minimum variance, and finally uses the separation signal of the separation weight vector. It doesn't need the fastest descent iteration to the cost function, so that it avoids the algorithm divergence due to the iterative step unreasonably set. Through simulation experiments, it shows that the algorithm proposed in this paper has the characteristics of high reliability and good noise suppression without having to estimate the source signal number, whether it is a sudden source signal or a non-sudden source signal. By increasing the array element number, the noise can be better suppressed, and the algorithm has good engineering value.

ACKNOWLEDGEMENT

This research was financially supported by fund of the project of improving the basic scientific research ability of young and middle-aged teachers in Guangxi Universities (2020KY80008) and "BAGUI Scholar" Program of Guangxi Zhuang Autonomous Region of China (201979) .

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