Mixing Matrix Estimation of Frequency Hopping Signals Based on Single Source Points Detection

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***Abstract*—To improve the mixing matrix estimation performance of frequency hopping (FH) signals under the underdetermined blind source separation (UBSS) model, a new estimation method is proposed in this paper. First, time frequency (TF) analysis is utilized to obtain sparse TF data. Then, remove the low-energy TF points to avoid the effect of noises and reduce the amount of calculation. Next, detect the single source points (SSPs) with the derived formula. Finally, the dynamic data field clustering method is utilized to estimate the mixing matrix. The results of simulation experiments indicate that the proposed algorithm has better performance than the compared algorithms.**

Keywords*—*FH signals, UBSS, SSP detection, mixing matrix estimation

I. INTRODUCTION

FH communication has been widely used in military and civil field due to its advantages, such as low intercept probability, good anti-jamming performance, excellent confidentiality performance and so on[1]. To get useful information, we usually need to separate source signals from FH signal mixtures or sort FH stations. So, blind source separation (BSS) technology can be very helpful to FH signal processing. UBSS model is utilized in this paper. Sparse component analysis (SCA) is the main method to solve UBSS problems. We can separate signals according to SCA method or sort signals directly based on the directions of arrival (DOAs) which are included in the mixing matrix. Therefore, the mixing matrix estimation of FH signals in synchronous orthogonal network is mainly discussed in this paper.

SCA was firstly utilized to separate multiple FH signals in [3]. However, the method has heavy computing burden, and has poor anti-noise performance. UBSS of FH signals in synchronous orthogonal network is studied in [4]. But the result of SSP detection is not satisfactory, and the performance of the algorithm is bad. A novel filtering method is introduced to separate FH signals in [5]. The method makes signal sparse by filtering instead of TF transform. A more effective SSP detection method is proposed in [6] but the clustering algorithm used in the article is not very accurate.

II. UBSS MODEL

Assume that N FH signals impinging on a uniform linear array (ULA) with M antennas. The signal reception model is shown in Fig. 1.

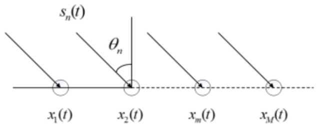

Fig. 1. Anti-jamming scenario of wireless communication system

The nth source signal $s_n(t)$ can be expressed as

$$s_n(t) = b_n(t)e^{j[\omega_n(t)t+\varphi_n(t)]}, n = 1,2,\ldots,N \tag{0}$$

where $b_n(t)$ is the amplitude of $s_n(t)$. $\omega_n(t)$ and $\varphi_n(t)$ are frequency and phase, respectively. Concerning that N source signals are received by the mth antenna under the condition of no noise, the observation signal $x_m(t)$ can be written as

$$x_m(t) = \sum_{n=1}^{N} s_n(t-\tau_{mn}) = \sum_{n=1}^{N} s_n(t)e^{-j\omega_n(t)\tau_{mn}} \tag{2}$$

So, the receiving signal matrix can be written as

$$\mathbf{x}(t) = \mathbf{A}(t)\mathbf{s}(t) \tag{3}$$

where $\mathbf{x}(t) = [x_1(t),\ldots,x_M(t)]^{\mathrm{T}}$ and $\mathbf{s}(t) = [s_1(t),\ldots,s_N(t)]^{\mathrm{T}}$. $\mathbf{A}(t) = [\mathbf{a}_1,\mathbf{a}_2,\ldots,\mathbf{a}_N] \in C^{M\times N}$ is the mixing matrix whose (m,n)th element is $a_{mn}(t) = e^{-j\omega_n(t)\tau_{mn}} = e^{-j2\pi f_n(t)\tau_{mn}}$.

According to the equation (3), we can get $\mathbf{x}(t)$ in matrix form:

$$\begin{bmatrix} x_1(t) \\ \vdots \\ x_M(t) \end{bmatrix} = \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \cdots & \vdots \\ e^{-j2\pi f_1(t)\tau_{M1}} & \cdots & e^{-j2\pi f_N(t)\tau_{MN}} \end{bmatrix} \begin{bmatrix} s_1(t) \\ \vdots \\ s_N(t) \end{bmatrix} \tag{4}$$

III. PROPOSED ALGORITHM

Assume that the number of antennas and source signals is 2 and 3, respectively. The TF matrix can be written as

$$\begin{bmatrix} X_1(t,f) \\ X_2(t,f) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \begin{bmatrix} S_1(t,f) \\ S_2(t,f) \\ S_3(t,f) \end{bmatrix} \tag{5}$$

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Assume that only one source signal $s_1(t)$ is active at TF point (t_p, f_q). Then, we can get

$$\left|\frac{X_2(t_p,f_q)}{X_1(t_p,f_q)}\right| - \left|\frac{X_1(t_p,f_q)}{X_2(t_p,f_q)}\right| = 0 \qquad (6)$$

Consider the effect of noise and relax the condition, ε is introduced:

$$\left\|\frac{X_2(t_p,f_q)}{X_1(t_p,f_q)}\right| - \left|\frac{X_1(t_p,f_q)}{X_2(t_p,f_q)}\right\| < \varepsilon \qquad (7)$$

The potential function $\varphi(x)$ is defined as:

$$\varphi(x) = \sum_{x_i \in D} mass_i \cdot e^{-\frac{\|x-x_i\|^2}{\beta^2}} \qquad (8)$$

where D is the initial data set and $mass_i$ is the quality of the ith point. Assume that the quality of all points is one, and the quality of each point is the same, which means $mass_i = 1/l, (i = 1,2,\ldots,l)$, l is the number of elements in D.

After obtaining re and im, the estimation of $\mathbf{A}(t)$ can be written as

$$\mathbf{A}_E = \begin{bmatrix} 1 & 1 & 1 \\ re_{21} + im_{21}j & re_{22} + im_{22}j & re_{23} + im_{23}j \end{bmatrix} \qquad (9)$$

In summary, the steps of the algorithm are outlined below: 1. Divide the signals into segments and signals are processed by STFT; 2. Eliminate the low-energy TF points; 3. Detect SSPs with formula (7); 4. Cluster re and im with dynamic data field clustering method and estimate the matrix $\mathbf{A}_E$ with formula (9).

IV. EXPERIMENTS

In the experiments, the number of antennas and signals is 2 and 3, respectively. The sampling frequency is 20MHz and the hop rate is 1000 hop/s. The incident angles are $20°, 60°, 80°$. The scatter of re and im before and after SSP detection and the TF points present obvious clustering feature is shown in Fig. 2.

Normalized mean square error in different SNRs is shown in Fig. 3. Comparing the proposed algorithm with algorithms in [5] and [6], it can be seen that our method has lower NMSE. The proposed SSPs detection method make TF data more sparse, and the dynamic data field clustering method improves the clustering performance. The experiment shows that the proposed algorithm is superior to the other two algorithms.

V. CONCLUSION

In order to improve the mixing matrix estimation performance of the FH signals in synchronous orthogonal network, a novel algorithm based on SSP detection is proposed. A SSP detection criterion is derived to obtain sparser TF points, and dynamic data field clustering method is introduced to improve the clustering performance. Simulation result shows that the algorithm has better performance

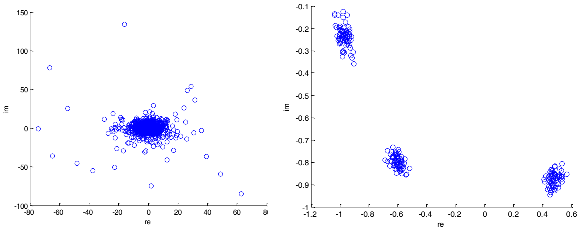

Fig. 2. The scatter of *re* and *im* before(left figure) and after(right figure) SSP detection

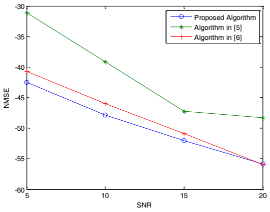

Fig. 3. The NMSE comparison of different algorithms at different SNRs

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