Multi-mainlobe Interferences Suppression Based on Interference Covariance Matrix Reconstruction

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Abstract. Here a novel eigen-projection matrix preprocessing (EMP) technology in view of covariance matrix rebuilding is presented. The eigenvectors of multiple mainlobe interferences are calculated via the correlation of eigenvectors between the sample covariance matrix (SCM) and this reconstructed mainlobe interference-plus-noise covariance matrix (IPNCM). Simulation consequents exhibit the excellence of this presented technique over this normal EMP method.

1 Introduction

In the array signal treatment, an adaptive beam-forming technology is one of the general tasks [1][2]. As an effective technique, adaptive beamforming method has a better performance among the other methods. At present, it’s receiving universal attention and research, and is widely used in the field of anti-interference. However, the mainlobe interference dramatically causes substantial degradation of the adaptive beamforming performance [3].

The blocking matrix preprocessing (BMP) [4][5] and the eigen-projection matrix pretreatment (EMP) [6][7] methods have been presented to get rid of this adverse effects of the main-lobe intrusion. Unfortunately, this BMP technique will degrade the free degree, and the EMP method will erroneously estimate eigenvector of the mainlobe interference probably for the case where multi-mainlobe interferences and sidelobe interferences exist simultaneously. Also, in view of big foramen auxiliary array, there is a novel technology aimed at suppressing main-lobe intrusion has been presented in [8].

In this letter, a new EMP method is presented for ameliorating the robustness of suppressing multi-mainlobe interference via the correlation of eigenvectors between the SCM and the reconstructed IPNCM [9][10][11]. Simulation consequents exhibit that the presented method has better presentation than conventional EMP method. Moreover, we compared the novel EMP method with the optimum and the sample matrix inverse (SMI) method, which also prove the superiority of the presented method.

2 Signal model

Suppose there is a uniform linear array (ULA), containing \( M \) elements entrenched by \( Q + P \)
narrowband uncorrelated signals (where $Q$ is mainlobe interferences and $P$ is sidelobe interferences, simultaneously $Q + P < M$). The standard snapshots at this $k$th time instant can be written as

$$x(k) = x_i(k) + n(k) = \sum_{i=1}^{Q+P} s_i(k)a(\theta_i) + n(k)$$

where $x_i(k)$ and $n(k)$ are $M \times 1$ vectors, which indicates the interference and noise respectively, $\theta_i$ is the $i$th interference direction-of-arrival (DOA), and the corresponding complex envelope and steering vector is $s_i(k)$ and $a(\theta_i)$, respectively. Assume the interferences and the noise are statistically independent. Write this theoretical IPNCM of the received signal as

$$R = E[x(k)x_H^H(k)] = \sum_{i=1}^{Q+P} p_i a(\theta_i)a^H(\theta_i) + \sigma_n^2 I$$

where $p_i$ and $\sigma_n^2$ denotes this power of the $i$th interference and noise, separately; and $(\cdot)^H$ denotes conjugate transpose. In order to suppress mainlobe interferences, the EMP method adopts an eigen-projection matrix $B$ to pretreat the received signal. It can get the preprocessing data as

$$y(k) = Bx(k)$$

Then, the covariance matrix of the pretreating data can be written as

$$R_y = E[y(k)y_H^H(k)] = E[BB^H(k)B^H] = BB^H$$

Based on minimum variance principle, calculate the typical adaptive weight vector as

$$w = \frac{R_y^{-1}a(\theta_0)}{a^H(\theta_0)R_y^{-1}a(\theta_0)}$$

where $a(\theta_0)$ denotes the steering vector of the expected signal. Since $R$ isn’t accessible in practice, it’s normally substituted in (4) by this covariance matrix of sample data

$$\hat{R} = \frac{1}{K}\sum_{k=1}^{K}x(k)x_H^H(k)$$

where $K$ denotes this number of received snapshot vectors. As the most important part, this eigen-projection matrix $B$ can be obtained by

$$B = I - U_m(U_m^H U_m)^{-1}U_m^H$$

where $I$ denotes the identity matrix, $U_m = [u_1, u_2, \ldots, u_Q]$ denotes the set of eigenvectors of mainlobe interferences. $u_m (m = 1, 2, \ldots, Q)$ is estimated by

$$|u_m^H a(\theta_i)|^2 > \rho$$

where $u_i(i = 1, 2, \ldots, Q + P)$ denote the interferences eigenvectors of the SCM, and $\rho$ is an suitable positive scalar factor, that is hard to be determined in actual application. Even worse, when there are more than one mainlobe interference and multi-sidelobe interferences coexist, the estimation of eigenvectors of multiple mainlobe interferences become inaccurate because of the noise.

3 Proposed method

In [12], the reconstructed mainlobe IPNCM can be obtained by

$$\hat{R}_w = \int_\Theta P(\theta)a(\theta)a^H(\theta)d\theta$$

where $\Theta$ is an angular sector in which the mainbeam is located, $P(\theta)$ denotes Capon spatial spectrum, and it can be expressed as

$$P(\theta) = \frac{1}{a^H(\theta)\hat{R}^{-1}a(\theta)}$$
Consequently, the matrix $\hat{R}_m$ is composed of eigenvectors of mainlobe interferences, moreover, we can be eigen-decompose the matrix $\hat{R}_m$ as

$$\hat{R}_m = \sum_{j=1}^{M} \hat{\lambda}_j \hat{u}_j \hat{u}_j^H$$

(11)

where $\hat{\lambda}_j$ ($j = 1, 2, \ldots, M$) are the eigenvalues of the matrix $\hat{R}_m$ sorted in descending order, $\hat{u}_j$ is the eigenvector associated with $\hat{\lambda}_j$.

In order to reduce the impact of the reconstructed mainlobe IPNCM, we use the correlation of mainlobe interferences eigenvectors between the SCM and the reconstructed mainlobe IPNCM to obtain the mainlobe interferences eigenvectors in the interference subspace of the SCM. If $\hat{u}_j$ and $u_i$ correspond to the same mainlobe interference,

$$\hat{u}_j^H u_i \approx 1$$

(12)

otherwise,

$$\hat{u}_j^H u_i \approx 0$$

(13)

Then a new set $U_m'$ is obtained by (12), and the modified eigen-projection matrix $B'$ can be given by (7). Therefore, write the adaptive optimal weight vector as

$$w' = \frac{(B'\hat{R}B'^H)^{-1} a(\theta_L)}{a^H(\theta_L)(B'\hat{R}B'^H)^{-1} a(\theta_L)}$$

(14)

4 Simulation

In the part, we execute a number of simulations to formalize the productiveness and advantage of the presented algorithm. Using a uniform linear array of $M = 20$ components with half-wave-length spacing. Suppose the array noise is a Gaussian white noise with a mean of zero and unit variation, which is spatially and temporally independent and considered as additive noise in elements. The direction of mainlobe is regarded as $0^\circ$. There are two mainlobe interference signals, which are setted to have DOAs $-1^\circ$ and $1.5^\circ$, and two sidelobe interference signals that are assumed to have DOAs $-15^\circ$ and $20^\circ$, respectively. The interference-to-noise ratios (INRs) are set artificially to be 20, 20, 50, and 50 dB in $-1^\circ$, $1.5^\circ$, $-15^\circ$ and $20^\circ$, respectively. The array adaptive pattern can be acquired by a Monte Carlo simulation. And it’s available for one simulation to take a snapshot of 50. In order to compare the output signal-to-interference-plus-noise ratio (SINR) of different methods versus the input signal-to-noise ratio (SNR), we can fix $K = 50$, which means snapshots. With the input SNR set as 10 dB, this output SINR is compared with this number of snapshots. Especially, 100 Monte Carlo experiments on average per simulation.

The different adaptive array patterns in one simulation are shown in Fig.1.

Fig.1. Adaptive array patterns of different methods for two mainlobe interferences suppression
Fig. 1 shows that the presented method has the best performance in suppressing not only mainlobe but also sidelobe interferences. By contrast, the SMI method suffers mainlobe distortion and the conventional EMP method suffers substantial degradation of sidelobe interferences suppression.

![Fig.2. Output SINR of different methods versus input SNR](image)

Fig. 2 displays output SINR of different methods and the optimal output SINR versus input SNR. Obviously, the trend of output SINR variation of different methods is similar to that of the optimum in the set range of input SNR, and the output SINR of the presented method is more close to the optimal SINR. In another word, the presented method has a better presentation than the other algorithms mentioned.

Due to the estimated matrix $\hat{R}$ is used to instead of the theoretical matrix $R$, this number of snapshots will affect this output SINR. The influence on the output SINR is shown in Fig. 3. The results from Fig. 3 show that no matter how $K$ changes, the output SINR of the presented method is always close to the optimal SINR. That is to say, the presented method outperforms the other methods. Moreover, the convergence rate of proposed algorithms enjoy much faster compared with SMI method, but similar to the conventional EMP method.

![Fig.3. Output SINR of different methods versus number of snapshots](image)

5 Conclusion

In this paper, a new type of EMP algorithm to improve the performance of multiple mainlobe interferences is presented, that is in view of the mainlobe IPNCM reconstruction. Overall, the presented method has a more effective performance than the SMI technology and the conventional EMP technology, and extensive simulations were executed to decorate the better performance of the presented algorithm in interference suppression.

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