Robust Weak Signal Detection and Bearing Estimation

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Abstract—**Robust weak signal detection is quite a difficult problem in the presence of interferences and noise. Generally, adaptive beamforming is an efficient way of interference suppression. However, conventional adaptive beamforming, e.g. MVDR may degrade significantly due to mismatch in the practical applications. In this paper, a robust adaptive interference suppression method is presented and then the worst-case performance optimization is implemented on the eigenanalysis-based re-constructed covariance matrix. Experimental results show the proposed method can efficiently suppress the interferences and then be for robust adaptive beamforming and weak signal detection.**

Keywords—Adaptive interference suppression; eigenanalysis; worst-case performance optimization; convex optimization

I. INTRODUCTION

Direction of arrival (DOA) estimation is of great interest in signal detection and parameter estimation [1], [2]. In practice, weak signal detection in the context of strong interferences is quite a difficult problem in Sonar localization. Therefore, much research work on interference suppression has been done [3]-[8]. Adaptive beamforming (ABF) is a widely used technique for interferences suppression and most of the ABF algorithms are based on the minimum variance distortionless response (MVDR) algorithm [9]. The similar operation on the space-time covariance matrix (STCM) is the matrix inversion (DMI) [10] or sample matrix inversion [[11], ch. 3]. The updated methods using the eigenanalysis theory are developed to be a powerful technique for interference suppression [12]. Dominant mode rejection (DMR) [13] is also an effective eigenanalysis-based interference suppression. Tufts *et al.* [3] firstly propose the principal components inversion (PCI) method in the case that a low-rank Gaussian signal is corrupted by colored Gaussian noise. Kirsteins *et al.* [14] investigate the performance of PCI by the probability density of the signal-to-noise ratio (SNR) [15]. In both DMR and PCI, the interference is supposed to be much stronger than the target of interest (TOI), so the dominant modes in DMR or the principal components in PCI are the eigencomponents with larger eigenvalues.

However, the performance of MVDR-based ABF may degrade comparatively in the presence of mismatch attributed to elements position error of the array or a poorly estimated covariance matrix. In many practical applications, the TOI-free STCM is hard to obtain and thus, the TOI will be suppressed as an interference due to the mismatch. To overcome the shortcoming, a modification on indirect matrix inversion ABF is developed and Cox *et al.* [16] propose a threshold to select the certain eigencomponents to suppress so that the mainlobe is protected. The eigencomponent association (ECA) method in [17] adaptively identifies the interference-related dominant components in the STCM by the proposed power ratio factor. *A priori* knowledge on the specific bearing of the TOI is required in these methods. However, it is always impossible to get the bearing of the TOI in the context of strong interference and mismatch in practice, especially when the bearing of the interference is adjacent to that of the TOI.

Besides the indirect matrix inversion ABF, many other robust ABF against mismatch has been developed [18]-[24]. Cox *et al.* [20] and Carlson [21] propose the diagonal loading method on the STCM to protect the beam response against the mismatch. Moreover, convex optimization emerges in the robust ABF as a major signal processing tool and makes significant impact because of its foundational nature and potential ability in signal processing [22]. Then the white noise gain constraint method in [20] could be transformed to a particular convex optimization problem, known as the norm-constrained capon beamforming [[11], ch. 3]. Vorobyov *et al.* [23] propose the robust ABF algorithm using worst-case performance optimization (WCPO) as a solution to the mismatch problem. And in [24], the robust Capon beamforming is proposed in the covariance fitting point of view and it is proved to have the same results as the WCPO ABF [[11], ch. 3]. Generally, these methods belong to the class of diagonal loading technique and the robustness of the adaptive beamformer is improved in the cost of the spatial resolution. Since the mainlobe of the strong interference is widened, weak signals may be corrupted by the adjacent strong interferences even in the adaptive way.

In this paper, a robust adaptive interference suppression (RAIS) method is proposed where the STCM is firstly re-constructed based on the eigenanalysis to suppress the strong interferences. A contribution ratio factor (CRF) is defined to remove the interference-dominated eigencomponents from STCM. A possible bearing interval that includes the bearing of the TOI is the only *priori* knowledge required in the proposed RAIS method. Moreover, the CRF in the proposed RAIS can identify the eigencomponents with a simply but robust threshold. Secondly, based on the proposed CRF, worst-case performance optimization on the re-constructed STCM

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improves the robustness against mismatch and detects the target efficiently. Experimental results show that the proposed technique suppresses interferences efficiently.

II. Eigenanalysis-based Robust Adaptive Beamforming

A. Data Model

The observation of an M-sensors array at time t is modeled as

$$\mathbf{x}(t) = s(t)\mathbf{a}(\theta_{\mathrm{s}}) + \sum_{k=1}^{K} d_k(t)\mathbf{a}(\theta_k) + \mathbf{n}(t), \quad (1)$$

where $s(t)$ and $d_k(t)$ are the narrow-band desired signal from the TOI and the k-th low-rank narrow-band interference, which are incoherent with each other; θ_{s} denotes the bearings of the TOI and θ_k is that of the k-th interference; $\mathbf{n} \in \mathbf{C}^{M\times 1}$ denotes the additive white Gaussian noise (AWGN); $\mathbf{a}(\theta) \in \mathbf{C}^{M\times 1}$ is the steering vector of the array in the bearing θ. Then the space-time covariance matrix (STCM) $\mathbf{R} \in \mathbf{C}^{M\times M}$ is expressed by

$$\mathbf{R} = \mathrm{E}\{\mathbf{x}\mathbf{x}^{\mathrm{H}}\} = P_{\mathrm{s}}\mathbf{a}(\theta_{\mathrm{s}})\mathbf{a}^{\mathrm{H}}(\theta_{\mathrm{s}}) + \sum_{k=1}^{K} P_{\mathrm{i}_k}\mathbf{a}(\theta_k)\mathbf{a}^{\mathrm{H}}(\theta_k) + \sigma_{\mathrm{n}}^2\mathbf{I}_M, \quad (2)$$

where P_{s} and P_{i_k} are the power of the TOI and the k-th interference, respectively; $\mathbf{I}_M$ denotes the M-dimension identity matrix; σ_{n}^2 is the variance of the AWGN. $\mathrm{E}\{\cdot\}$ and $(\cdot)^{\mathrm{H}}$ denote the statistical expectation and the Hermitian transpose of a vector or a matrix, respectively. The eigendecomposition of $\mathbf{R}$ is presented as

$$\mathbf{R} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{\mathrm{H}} = \sum_{m=1}^{M} \lambda_m \mathbf{v}_m \mathbf{v}_m^{\mathrm{H}}, \quad (3)$$

where $\mathbf{V} = [\mathbf{v}_1, \ \mathbf{v}_2, \ \cdots, \ \mathbf{v}_M]$, $\mathbf{\Lambda} = \mathrm{diag}\{\lambda_1, \lambda_2, \cdots, \lambda_M\}$, $\mathbf{v}_m \in \mathbf{C}^{M\times 1}$ and λ_m are the m-th eigenvector and eigenvalue of $\mathbf{R}$, respectively. Assuming the eigenvalues are in descendent order without loss in generality, it is easy to get that

$$\lambda_1 > \lambda_2 > \cdots > \lambda_{K+1} > \lambda_{K+2} = \cdots = \lambda_M = \sigma_n^2 > 0. \quad (4)$$

Then, the eigenvectors corresponding to the first $K+1$ eigenvalues are called the dominant modes in DMR or the principle components in PCI which span the signal and interference subspace $\mathbf{V}_{\mathrm{s}} \in \mathbf{C}^{M\times(K+1)}$ and the last $M-K-1$ eigenvectors span the noise subspace $\mathbf{V}_{\mathrm{n}} \in \mathbf{C}^{M\times(M-K-1)}$.

B. Eigenanalysis-based Interference Suppression

The single eigenvector beamforming is defined as

$$\mathbf{P}_m(\theta) = \mathbf{w}^{\mathrm{H}}(\theta)\mathbf{v}_m\mathbf{v}_m^{\mathrm{H}}\mathbf{w}(\theta), \quad (5)$$

where $\mathbf{w}(\theta) = \mathbf{a}(\theta)/M$ is the weight vector of the conventional beamforming (CBF). $\mathbf{P}_m$ represents the spatial spectrum of $\mathbf{v}_m$ which can show the dominant contributor of the m-th eigenvector. If the dominant contributor of each eigenvector could be identified, we will be able to suppress the interference by removing the interference-dominated eigenvectors from the STCM.

In order to identify which eigencomponent is dominantly contributed by the TOI, *a priori* knowledge about the bearing of the TOI θ_{s} is required. Considering that the accurate bearing of the TOI is often difficult to obtain, we assume that $\theta_{\mathrm{s}} \in \Theta = [\theta_{\mathrm{L}} \quad \theta_{\mathrm{R}}]$, where Θ is the possible bearing interval. Obviously, the requirement on *a priori* knowledge about the possible bearing interval is much less than that in [16],[17].

By computing the beamforming of each eigenvector through Θ and the entire bearing space Θ_{E}, e.g. from 0 degree to 180 degree for the linear uniformed array (ULA), a contribution ratio factor (CRF) is defined as

$$\eta_m = \frac{\max_{\theta\in\Theta}\{\mathbf{P}_m(\theta)\}}{\max_{\theta\in\Theta_{\mathrm{E}}}\{\mathbf{P}_m(\theta)\}}, \quad m = 1, 2, ..., M. \quad (6)$$

Some properties of the CRF are given as follows:

1) there is $\max_{\theta\in\Theta}\{\mathbf{P}_m(\theta)\} \le \max_{\theta\in\Theta_{\mathrm{E}}}\{\mathbf{P}_m(\theta)\}$, i.e. $\eta_m \le 1$, since $\Theta \subset \Theta_{\mathrm{E}}$.
2) Theoretically, if the dominant contribution of the m-th eigenvector $\mathbf{v}_m$ is from the TOI within the bearing interval Θ, we have $\eta_m = 1$ and then let $\mathbf{v}_m \in \mathbf{V}_\dagger$.
3) Generally, we assume that the interferences are not within the bearing interval Θ. If the dominantt contribution of the m-th eigenvector $\mathbf{v}_m$ is from the interferences, we have $\eta_m < 1$ and let $\mathbf{v}_m \in \mathbf{V}_\ddagger$.
4) If the dominant contribution of the m-th eigenvector $\mathbf{v}_m$ is from the noise (that is, $\mathbf{v}_m$ is in the noise subspace $\mathbf{V}_{\mathrm{n}}$), both $\eta_m < 1$ and $\eta_m = 1$ are possible due to its random properties. Thus, if $\eta_m = 1$, the corresponding eigenvectors will belong to $\mathbf{V}_\dagger$. However, the SNR can still be increased because some of the eigenvectors in the noise subspace will belong to $\mathbf{V}_\ddagger$ for $\eta_m < 1$.

Based on the proposed CRF, $\mathbf{V}$ is divided into two subspaces, i.e. $\mathbf{V}_\dagger \in \mathbf{C}^{M\times L}$ and $\mathbf{V}_\ddagger \in \mathbf{C}^{M\times(M-L)}$. Even in situations that the mismatch is present which leads to the inaccurate estimate of the TOI's bearing, the CRF is still functional as long as the possible bearing interval Θ still includes the inaccurate bearing estimate. Moreover, in many practical situations mismatch may lead to eigenspace disturbance [10]. In our proposed method, the CRF is robust against the eigenspace disturbance and can still separate $\mathbf{V}_\dagger$ and $\mathbf{V}_\ddagger$ apart.

Then we can re-construct the STCM based on the two subspaces as

$$\tilde{\mathbf{R}}_\dagger = \mathbf{V}_\dagger\mathbf{\Lambda}_\dagger\mathbf{V}_\dagger^{\mathrm{H}} \text{ and } \tilde{\mathbf{R}}_\ddagger = \mathbf{V}_\ddagger\mathbf{\Lambda}_\ddagger\mathbf{V}_\ddagger^{\mathrm{H}} \quad (7)$$

where $\mathbf{\Lambda}_\dagger \in \mathbf{C}^{L\times L}$ and $\mathbf{\Lambda}_\ddagger \in \mathbf{C}^{(M-L)\times(M-L)}$ are diagonal matrices containing the corresponding eigenvalues of the eigenvectors in $\mathbf{V}_\dagger$ and $\mathbf{V}_\ddagger$, respectively. The TOI is reserved in $\tilde{\mathbf{R}}_\dagger$ while the interferences out of the possible bearing interval are suppressed so that the TOI is detected more efficiently. $\tilde{\mathbf{R}}_{\ddagger}$ can be applied in the adaptive spatial filtering in case that the TOI is rejected as an interference in the presence of mismatch.

C. Implementation of Worst-case Performance Optimization

WCPO is a robust adaptive beamforming method [23] which generally outperforms other robust adaptive beamforming algorithms [11]. The cost function and the constraint in WCPO are as follow:

$$\begin{aligned} &\text{minimize} \quad \mathbf{w}^{\mathrm{H}}\mathbf{R}\mathbf{w} \\ &\text{subject to} \quad \left\|\mathbf{w}^{\mathrm{H}}\mathbf{c}(\theta)\right\| \geq 1 \ \text{ for all } \mathbf{c}(\theta) \in \Gamma(\varepsilon) \end{aligned} \tag{8}$$

where $\Gamma(\varepsilon) = \left\{\mathbf{c}(\theta) \mid \mathbf{c}(\theta) = \hat{\mathbf{a}}(\theta) + \mathbf{e},\ \|\mathbf{e}\| \leq \varepsilon\right\}$ and ε denotes the potential error between the steering vector of the model and the true steering vector. Instead of requiring fixed distortionless response towards the desired direction $\hat{\mathbf{a}}(\theta)$, such distortionless is now maintained by means of inequality constraint for all the possible steering vectors belonging to the spherical uncertainty set $\Gamma(\varepsilon)$ which ensures more robustness against many kinds of mismatch. However, the WCPO algorithm promises more robustness in the cost of spatial resolution. So the TOI may be buried in the wide mainlobe of the adjacent strong interferences. Thus, in this paper we combine the WCPO with the aforementioned re-constructed STCM $\tilde{\mathbf{R}}_{\dagger}$, where the interferences outside the possible bearing interval are suppressed and the cost function becomes

$$\begin{aligned} &\text{minimize} \quad \mathbf{w}^{\mathrm{H}}\tilde{\mathbf{R}}_{\dagger}\mathbf{w} \\ &\text{subject to} \quad \left\|\mathbf{w}^{\mathrm{H}}\mathbf{c}(\theta)\right\| \geq 1 \text{ for all } \mathbf{c}(\theta) \in \Gamma(\varepsilon). \end{aligned} \tag{9}$$

As defined in (7), $\tilde{\mathbf{R}}_{\dagger}$ is a positive semi-definite matrix. So the cost function $\mathbf{w}^{\mathrm{H}}\tilde{\mathbf{R}}_{\dagger}\mathbf{w}$ is still a convex one which could be applied in convex optimization [25]. However, the constraint in (9) still appears to computationally intractable. According to [22], [23], the constraint in (9) can be transformed to

$$\begin{aligned} &\text{minimize} \quad \mathbf{w}^{\mathrm{H}}\tilde{\mathbf{R}}_{\dagger}\mathbf{w} \\ &\text{subject to} \quad \mathbf{w}^{\mathrm{H}}\hat{\mathbf{a}}(\theta) - \varepsilon\|\mathbf{w}\| \geq 1, \end{aligned} \tag{10}$$

which is a convex optimization problem and the convexity property ensures the optimization in some sense functional and stable, for example, any local optimum must be the global optimum.

Take the equality constraint in (9) to simplify the derivation and using the Lagrange multiplier method, the weight vector of the RAIS can be presented as

$$\mathbf{w}(\theta) = \beta\left(\tilde{\mathbf{R}}_{\dagger} + \frac{\beta\varepsilon}{\|\mathbf{w}\|}\mathbf{I}_M\right)^{-1}\hat{\mathbf{a}}(\theta) \tag{11}$$

where β is the Lagrange multiplier. It is clear that the RAIS method belongs to the class of the diagonal loading technique on the re-constructed STCM. Although the matrix $\tilde{\mathbf{R}}_{\dagger}$ is not full rank, the diagonal loading form $\tilde{\mathbf{R}}_{\dagger} + \beta\varepsilon\mathbf{I}_M/\|\mathbf{w}\|$ in (11) makes the re-constructed STCM invertible and ensures the algorithm being stable in the optimization process. However, it is unrealistic to apply (11) directly to compute the optimal weight vector in RAIS because the Lagrange multiplier β could be expressed in a closed form. To solve the problem, Eq. (10) could be transformed to the canonical second-order cone (SOC) programming problem that can be simply solved by standard and highly efficient interior point method software such as "Sedumi" [26] using the convex optimization programming language "Yalmip" [27].

III. Experimental Results

An experiment was carried out in the Yellow Sea in 2005. A 43-sensors horizontal array spaced at about 1.5m is deployed for the signal detection. The estimates of elements positions are illustrated in Fig.1. There are some mismatch errors since the true positions of array elements may be changed by the ocean wave and current. Some elements do not work, and their invalid data is removed from the observation. The sound velocity profile (SVP) in the experiment area is shown in Fig.2. The frequency rang of interest is 100Hz to 200Hz.

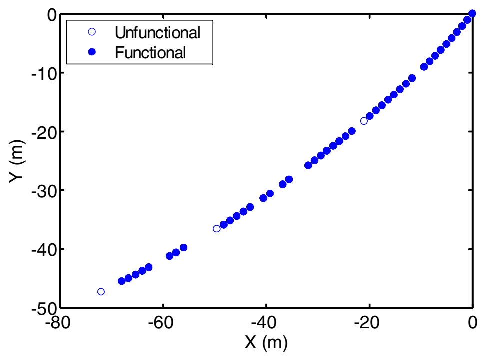

Fig.1. Deployment of the horizontal array.

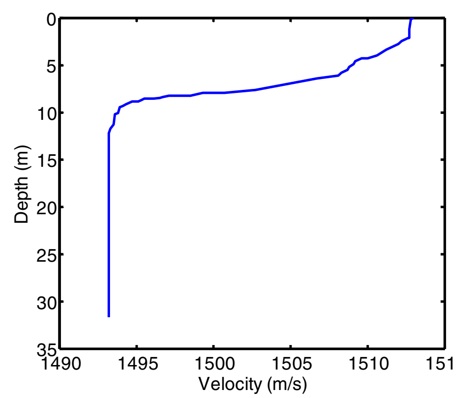

Fig.2. Sound velocity profile.

The DOA estimation results with CBF are illustrated in Fig.3. The cooperative target is at the bearing around 120°. The SNR decreases as the TOI goes far away. The strong interference sources appear at the bearing around 30° and 240°. The results of the proposed method in this paper are illustrated in Fig.4, where the target is efficiently detected. The background is much clearer in comparison with that of the CBF in Fig.3. The interference is not suppressed significantly at around the 5th minute since the power of the interference is very close to that of the TOI, and the detailed reason is shown in [28].

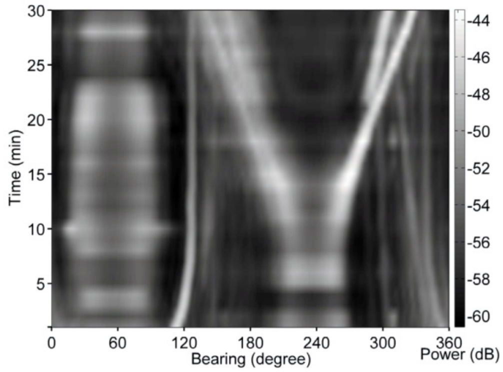

Fig. 3. DOA estimates by CBF

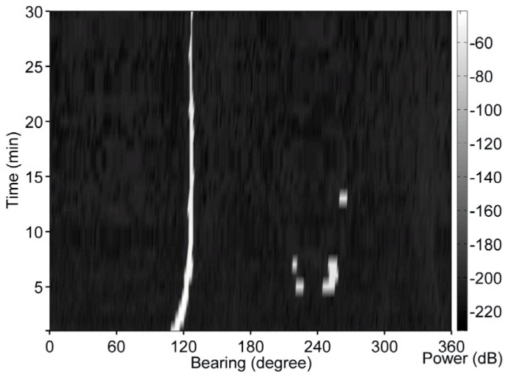

Fig. 4. DOA estimates by the proposed method, $\varepsilon = 3$ and Θ is adaptively adjusted based on the last result.

IV. Conclusions

In this paper, a robust adaptive beamforming method is proposed based on the eigenanalysis. The STCM is re-constructed to separate the TOI-dominated eigenvector from the interference-dominated eigenvectors, using a more stable and practical criterion. Worst-case performance optimization is directly implemented on the re-constructed STCM to improve the robustness against mismatch. The contribution ratio is defined to identify the TOI and the interference subspace. The proposed method successfully detects the weak target corrupted by the adjacent strong interference even in the presence of mismatch. The proposed method has higher SINR. It is not sensitive to the diagonal loading factor. The experimental results also show that the proposed method suppresses interference efficiently and is robust against mismatch in practical applications.

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