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Robust Vehicle Localization Exploiting Two Based Stations Cooperation: A MIMO Radar Perspective

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ABSTRACT Autonomous vehicles depend on global positioning systems' aided by motion sensors to estimate its position within the traffic network. However, all the driving vehicles cannot be ensured to have satellite visibility. Therefore, in order to increase the accuracy and robustness of vehicle localization, it is important to have an assistant localization method for these systems by using some environmental sensing, such as cameras and radars. In this paper, we look at using multiple-input multiple-output (MIMO) radar for vehicle localization. The performance of cross localization in MIMO radar relies on the accuracy of the direction of arrival (DOA) estimation. But the performance of most existing DOA estimation methods based on sparse signal recover is affected by the unknown nonuniform noise and mutual coupling. The proposed method uses a linear transformation to eliminate the influence of mutual coupling by utilizing the banded complex symmetric Toeplitz structure of the mutual coupling matrices in both transmit and receive arrays. Then, a real-valued covariance vector-based sparse Bayesian learning framework is formulated for DOA estimation by utilizing the unitary transformation, in which the variances of nonuniform noise can be updated by using the least square strategy. The proposed method can work well and provide better DOA estimation performance than the existing sparse signal recover-based algorithms in unknown mutual coupling and nonuniform noise. Simulation results are provided to demonstrate the advantage of the proposed method.

INDEX TERMS Vehicle localization, MIMO radar, mutual coupling, nonuniform noise, sparse Bayesian learning.

I. INTRODUCTION

In recent years, the development of autonomous vehicles has drawn a lot of attention, and the vehicles localization in traffic network is a fundamental aspect for autonomous driving vehicles [1]. In general, the global positioning systems (GPS) is the first selection for vehicle localization, and it can provide accuracy well sufficient for vehicles localization when the GPS is available [2]. However, when the driving vehicles in some places, such as near tall building or in tunnels, the GPS systems is not available. Thus, the other assistant localization method for these systems by utilizing some environmental sensing, such as cameras, radar and so on, is arisen [3]. The localization methods based on radar system are the most important way due to the fact that it is not affected with the weather and light. In radar system, the cross localization is an efficient scheme for vehicle localization, which depends on the accurate of direction of arrival (DOA) estimation [4], [5]. But the conventional radars, including phased array radar, have limited DOA estimation performance, especially for close spaced sources [6]–[8].

In recent years, the multiple input multiple output (MIMO) radar systems have been considered as a promising prospect of radar system due to its potential advantages, such as more degree of freedoms (DOFs), higher spatial resolution and parameter estimation performance [9]–[11]. According to the literatures published in the past few years, for MIMO radar system, most of the DOA estimation can be grouped into two classes: the subspace technique based algorithms [12]–[17]

and sparse signal recover (SSR) based algorithms [18]–[22]. For the subspace technique based algorithms, the signal/noise subspace is required to estimate from the eigenvalue decomposition (EVD) of the covariance matrix, such as the MUSIC based algorithms and ESPRIT algorithms. In order to achieve the accurate covariance matrix, the SNR is required as higher enough and the number of snapshots is reasonable large. Thus, the subspace technique based methods have performance degradation even fail to work when the SNR is lower and the number of snapshots is limited. On the other hand, the SSR-based algorithms are proposed in the past few years, which use the SSR technique to recover a sparse spatial spectrum for DOA estimation. The simulation results have been verified that the SSR based algorithms have the capacity to fit the case of low SNR or/and limited snapshots, and provide superior performance than subspace technique based algorithms.

For MIMO radar, in practice, the influent of the mutual coupling may exist between the elements and the received noise is nonuniform noise, due to the imperfectly-calibrated transmit and receive arrays [23]–[25]. The conventional SSR-based methods have performance degradation or fail to work due to the fact that these methods rely on the perfect array manifold and Gaussian white noise. In order to achieve the accurate estimation performance with the SSR framework, an efficient sparse signal recover method is formulated for DOA estimation in [26], in which the banded complex symmetric Toeplitz structure of the mutual coupling matrices is utilized to remove the effect of mutual coupling. But the drawback of this method is that it leads aperture loss. In order to improve the estimation performance, a spare representation of covariance vector scheme is also proposed for eliminating the mutual coupling in MIMO radar [20], and the fourth-order cumulants-based SSR scheme is also investigated in this case [27]. On the other hand, considering the influence of nonuniform noise, a robust covariance sparsity-aware DOA estimation algorithm is proposed in [28], but the estimation performance is limited due the drawback of l_1 norm optimization and the aperture loss. In order to avoid the drawback, a sparse bayesian learning strategy is investigated without aperture loss in MIMO radar [29], and it achieves superior performance than the method in [28]. According to the above analysis, the existing SSR based algorithms treat the mutual coupling and nonuniform noise independently, which indicates that these method may have remarkable performance degradation or fail to work with the coexist of unknown mutual coupling and nonuniform noise. To the best of our knowledge, in addition, there are few literatures on consideration of the SSR based DOA estimation with the coexist of unknown mutual coupling and nonuniform noise.

In this paper, in order to solve the DOA estimation for vehicle localization in MIMO radar in the presence of unknown mutual coupling and nonuniform noise, a robust unitary sparse bayesian learning (USBL) is proposed. According to the banded complex symmetric Toeplitz structure of the mutual coupling matrices in MIMO arrays, the proposed method firstly eliminates the mutual coupling effect by using a linear transformation. Then a real-valued covariance vector is achieved by using the unitary transformation, and a robust unitary sparse bayesian learning strategy is formulated for DOA estimation, in which least square(LS) strategy is adopted to update the variances of nonuniform noise for suppressing the influence of nonuniform noise. Thus, the proposed method can perform well in the presence of unknown mutual coupling and nonuniform noise. Furthermore, the proposed method exhibits superior performance than the existing sparse signal recover based algorithms.

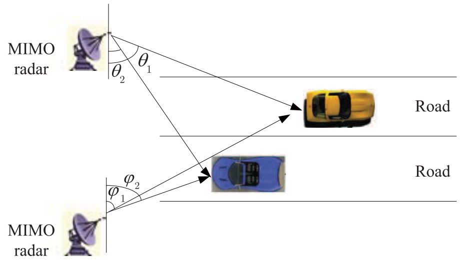

FIGURE 1. The cross localization of vehicle with two cooperation MIMO radars.

The remainder of this paper is organized as follows. The MIMO radar signal mode for vehicle localization is elaborated in Section II. The proposed robust unitary SBL is presented in Section III, and some related remarks are investigated in Section IV. Section V gives the simulation results. Section VI concludes the paper.

Notation: $\mathbf{I}_K$ denotes a $K \times K$ identity matrix. Π_k denotes the $k \times k$ exchange matrix with ones on its anti-diagonal and zeros elsewhere. $\otimes$ denotes the Kronecker product, and $\odot$ represents the Khatri-Rao product. $diag\{\mathbf{a}\}$ denotes a diagonal matrix with the diagonal entries from $\mathbf{a}$. $(\cdot)^{\mathrm{H}}$, $(\cdot)^{-1}$, $(\cdot)^*$, $(\cdot)^{\mathrm{T}}$, and $(\cdot)^+$ denote the conjugate-transpose, inverse, conjugate, transpose, and pseudo-inverse respectively. Vec$\{\cdot\}$ denotes the vectorization operation.

II. SIGNAL MODEL AND PROBLEM FORMULATION

Consider a cross localization of vehicle with two cooperation MIMO radars, shown in Fig.1, and two DOAs estimated by two MIMO radars is used for vehicle localization. In addition, two MIMO radars are implemented with the sam way, which indicates that only one MIMO radar is needed to describe for DOA estimation, and the other one works as the same way. In the cross localization scheme, one narrowband MIMO radar equipped with M transmit antennas and N receive antennas is considered, shown in Fig.2. The uniform linear arrays (ULAs) with half-wavelength spacing is used for the transmit and receive arrays. Furthermore, the transmit and receive arrays are located closely, which indicates that the angles of one vehicle respect to the normals of transmit and receive arrays are the same, and they are named as direction of arrival (DOA). In MIMO radar system, M orthogonal waveforms satisfied with $\boldsymbol{\phi}_i^{\mathrm{H}}\boldsymbol{\phi}_j = 0 (i \neq j)$ and $\boldsymbol{\phi}_i^{\mathrm{H}}\boldsymbol{\phi}_j = 1 (i = j)$

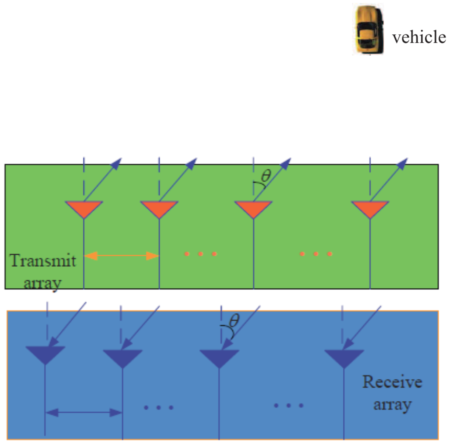

FIGURE 2. **The configuration of MIMO radar for vehicle localization.**

are emitted by the transmit antennas, which can be used for forming a group of matched filters at the receive array, where $\boldsymbol{\phi}_i$ denotes the waveform of the i transmit antennas. After using these matched filter to the received data, the received data can be written as [29]

$$\mathbf{y}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \tag{1}$$

where $\mathbf{y}(t) \in \mathbb{C}^{MN\times 1}$ is received data after using the matched filters, and $\mathbf{A} = [\mathbf{a}_t(\theta_1) \otimes \mathbf{a}_r(\theta_1), \cdots, \mathbf{a}_t(\theta_P) \otimes \mathbf{a}_r(\theta_P)]$ is the transmit-receive steering matrix, $\mathbf{a}_t(\theta_p) = [1, e^{j\sin\theta_p}, \cdots, e^{j(M-1)\sin\theta_p}]^{\mathrm{T}}$ and $\mathbf{a}_r(\theta_p) = [1, e^{j\sin\theta_p}, \cdots, e^{j(N-1)\sin\theta_p}]^{\mathrm{T}}$ are the transmit steering vector and receive steering vector, respectively. $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_P(t)]^{\mathrm{T}} \in \mathbb{C}^{P\times 1}$ is received signal vector composed with $s_p(t) = \beta_p(t)e^{j2\pi f_p(t)}$, in which $s_p(t) = \beta_p(t)e^{j2\pi f_p(t)}$ and $\beta_p(t)$ and $f_p(t)$ denote the scattering coefficient and Doppler frequency of the pth sources, respectively. Due to the imperfectly-calibrated transmit and receive arrays, the vector $\mathbf{n}(t) \in \mathbb{C}^{MN\times 1}$ is the nonuniform noise, and its covariance matrix is shown as [29]

$$\mathbf{R}_n = \mathbf{I}_M \otimes \mathbf{R}_{\bar{\mathbf{n}}} \tag{2}$$

where $\mathbf{R}_{\bar{\mathbf{n}}} = \mathrm{E}[\bar{\mathbf{n}}(l)\bar{\mathbf{n}}(l)^{\mathrm{H}}] = \mathrm{diag}\{[\sigma_1^2, \sigma_2^2, \cdots, \sigma_N^2]\}$. $\bar{\mathbf{n}}(l)$ is covariance matrix of nonuniform noise before matched filters, and σ_n^2 is the noise variance of the nth receive antennas, which satisfies $\sigma_1^2 \neq \sigma_2^2 \neq \cdots \neq \sigma_N^2$. The Eq.(1) shows the signal model with idea array manifold. Due to the mutual coupling effect in MIMO arrays, the mutual coupling matrices of transmit and receive arrays are modeled as a symmetric Toeplitz matrix, which can be expressed as

$$\begin{aligned} \mathbf{C}_t &= \mathrm{toeplitz}\left(\left[\mathbf{c}_t^T, \mathbf{0}_{1\times(M-K-1)}\right]\right) \in \mathrm{C}^{M\times M} \\ \mathbf{C}_r &= \mathrm{toeplitz}\left(\left[\mathbf{c}_r^T, \mathbf{0}_{1\times(N-K-1)}\right]\right) \in \mathrm{C}^{N\times N} \end{aligned} \tag{3}$$

where $c_{ik}(i = r, t; k = 0, 1, 2, \cdots, K)$ denotes the $K+1$ nonzero mutual coupling coefficients, and K satisfies $min\{M, N\} > 2K$. For the mutual coupling coefficient between two antennas, its value opposites to the distance of two antennas and equals to zeros when the distance is far enough, which can be shown as $0 < |c_{iK}| <, \cdots, < |c_{i1}| < |c_{i0}| = 1$. Based on the mutual coupling matrices shown in Eq.(3), the received signal in Eq.(1) can be revised as

$$\mathbf{y}(t) = \mathbf{C}\mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \tilde{\mathbf{A}}\mathbf{s}(t) + \mathbf{n}(t) \tag{4}$$

where $\mathbf{C} = \mathbf{C}_t \otimes \mathbf{C}_r$ is the transmit-receive mutual coupling matrix. and the novel transmit-receive steering matrix is $\tilde{\mathbf{A}} = \mathbf{C}\mathbf{A} = [\tilde{\mathbf{a}}_t(\theta_1) \otimes \tilde{\mathbf{a}}_r(\theta_1), \cdots, \tilde{\mathbf{a}}_t(\theta_P) \otimes \tilde{\mathbf{a}}_r(\theta_P)]$ with $\tilde{\mathbf{a}}_t(\theta_p) = \mathbf{C}_t\mathbf{a}_t(\theta_p)$ and $\tilde{\mathbf{a}}_r(\theta_p) = \mathbf{C}_r\mathbf{a}_r(\theta_p)$. By collecting the received data with J snapshots, the Eq.(4) can be rewritten as

$$\mathbf{X} = \tilde{\mathbf{A}}\mathbf{S} + \mathbf{N} \tag{5}$$

where $\mathbf{X} = [\mathbf{x}(t_1), \mathbf{x}(t_2), \cdots, \mathbf{x}(t_J)]$ is the received data matrix. $\mathbf{S} = [\mathbf{s}(t_1), \mathbf{s}(t_2), \cdots, \mathbf{s}(t_J)]$ is the signal matrix, and $\mathbf{N} = [\mathbf{n}(t_1), \mathbf{n}(t_2), \cdots, \mathbf{n}(t_J)]$ is the nonuniform noise matrix. For the Eq.(5), the conventional SSR based algorithm only consider the mutual coupling effect in the transmit-receive steering matrix $\tilde{\mathbf{A}}$ or the influence of the nonuniform noise. In the following section, the SSR based DOA estimation for vehicle localization is investigated with the coexist of unknown mutual coupling and nonuniform noise.

III. ROBUST SPARSE BAYESIAN LEARNING ALGORITHM FOR DOA ESTIMATION

Due to the coexist of unknown mutual coupling and nonuniform noise, the performance of the conventional DOA estimation methods have remarkable degradation, which indicants that the performance of vehicle localization is also degradation. Aiming at obtaining the desired performance, the mutual coupling and nonuniform noise effect must be avoided or eliminated firstly. Taking advantage of the symmetric Toeplitz structure of the mutual coupling matrices, two selection matrices are constructed for eliminating the influence, which are shown as

$$\begin{aligned} \mathbf{J}_1 &= \left[\mathbf{0}_{(M-2K)\times K}, \mathbf{I}_{(M-2K)}, \mathbf{0}_{(M-2K)\times K}\right] \\ \mathbf{J}_2 &= \left[\mathbf{0}_{(N-2K)\times K}, \mathbf{I}_{(N-2K)}, \mathbf{0}_{(N-2K)\times K}\right] \end{aligned} \tag{6}$$

Then the selection matrices can be applied to the transmit and receive steering matrices, respectively, which can be expressed as

$$\begin{cases} \hat{\mathbf{a}}_t\left(\theta_p\right) = \mathbf{J}_1\tilde{\mathbf{a}}_t\left(\theta_p\right) = \beta_{tp}\bar{\mathbf{a}}_t\left(\theta_p\right) \\ \hat{\mathbf{a}}_r\left(\theta_p\right) = \mathbf{J}_2\tilde{\mathbf{a}}_r\left(\theta_p\right) = \beta_{rp}\bar{\mathbf{a}}_r\left(\theta_p\right) \end{cases} \tag{7}$$

where $\bar{\mathbf{a}}_r(\theta_k)$ and $\bar{\mathbf{a}}_t(\theta_k)$ are the new steering vectors, which consist with the first $N-2K$ and $M-2K$ elements of $\mathbf{a}_r(\theta_k)$ and $\mathbf{a}_t(\theta_k)$, respectively. $\beta_{tp} = 1 + \sum_{k=1}^{K} 2c_{tk}\cos\left(p\pi\sin\theta_p\right)$ and $\beta_{rp} = 1 + \sum_{k=1}^{K} 2c_{rk}\cos\left(p\pi\sin\theta_p\right)$. According to the expression of β_{tp} and β_{rp}, it indicates that for the $p(p = 1, 2, \cdots, P)$th target, the parameter β_{tp} and β_{rp} are constant, which mens that the mutual coupling effect in transmit and receive arrays is eliminated. For the transmit-receive steering vector, the operation in Eq.(7) can be extended as

$$\begin{aligned} \hat{\mathbf{a}}_t(\theta_p) \otimes \hat{\mathbf{a}}_r(\theta_p) &= (\mathbf{J}_1 \otimes \mathbf{J}_2)(\tilde{\mathbf{a}}_t(\theta_p) \otimes \tilde{\mathbf{a}}_r(\theta_p)) \\ &= \beta_{rp}\beta_{tp}(\bar{\mathbf{a}}_t(\theta_p) \otimes \bar{\mathbf{a}}_r(\theta_p)) \end{aligned} \tag{8}$$

According to Eq.(8), the effect of mutual coupling between the transmit-receive elements is removed after using the linear transformation. Thus, this linear transformation can applied to the received data for the decoupling operation, which can be expressed as

$$\bar{\mathbf{X}} = (\mathbf{J}_1 \otimes \mathbf{J}_2)\mathbf{X} = \bar{\mathbf{A}}\bar{\mathbf{S}} + \bar{\mathbf{N}} \tag{9}$$

where $\bar{\mathbf{A}} = [\bar{\mathbf{a}}_t(\theta_1) \otimes \bar{\mathbf{a}}_r(\theta_1), \cdots, \bar{\mathbf{a}}_t(\theta_P) \otimes \bar{\mathbf{a}}_r(\theta_P)]$ denotes the new transmit-receive steering matrix after the decoupling operation, and the signal data matrix $\bar{\mathbf{S}} = \mathbf{DS}$ with $\mathbf{D} = \text{diag}(\beta_{r1}\beta_{t1}, \cdots, \beta_{rP}\beta_{tP})$. The noise matrix $\bar{\mathbf{N}} = (\mathbf{J}_1 \otimes \mathbf{J}_2)\mathbf{N}$ is also the nonuniform noise due to the inherent characteristics of the linear transformation. According to the structure of the transmit-receive steering vector $\bar{\mathbf{a}}_t(\theta) \otimes \bar{\mathbf{a}}_r(\theta)$, it is easy to show that there are some redundant elements, and it can be rewritten as

$$\bar{\mathbf{a}}_t(\theta) \otimes \bar{\mathbf{a}}_r(\theta) = \mathbf{G}\mathbf{b}(\theta) \tag{10}$$

where the transformation matrix $\mathbf{G}$ is shown as

$$\mathbf{G} = [\mathbf{J}_0^{\mathrm{T}}, \mathbf{J}_1^{\mathrm{T}}, \cdots, \mathbf{J}_{\bar{M}-1}^{\mathrm{T}}]^{\mathrm{T}} \tag{11}$$

$$\mathbf{J}_m = [\mathbf{0}_{\bar{N}\times m}, \mathbf{I}_{\bar{N}}, \mathbf{0}_{\bar{N}\times(\bar{M}-m-1)}] \quad m = 0, 1, \ldots, \bar{M}-1 \tag{12}$$

$$\mathbf{b}(\theta) = [1, \exp(j\pi\sin\theta), \cdots, \exp(j\pi(\bar{M}+\bar{N}-2)\sin\theta)]^{\mathrm{T}} \tag{13}$$

where $\bar{M} = \bar{M} - 2P$ and $\bar{N} = N - 2P$. According to the Eq.(10), a reduced dimension transformation matrix is constructed for eliminating the redundant elements in transmit-receive steering, which is shown as [16]

$$\mathbf{D} = (\mathbf{G}^{\mathrm{H}}\mathbf{G})^{-(1/2)}\mathbf{G}^{\mathbf{H}} \tag{14}$$

Then multiplying the reduced dimensional matrix $\mathbf{D}$ with the data matrix $\bar{\mathbf{X}}$ yields

$$\begin{aligned}\bar{\mathbf{Y}} &= \mathbf{D}\bar{\mathbf{X}} = (\mathbf{G}^{\mathrm{H}}\mathbf{G})^{(1/2)}\mathbf{B}\bar{\mathbf{S}} + \mathbf{D}\bar{\mathbf{N}} \\ &= \mathbf{F}^{(1/2)}\mathbf{B}\bar{\mathbf{S}} + \underline{\mathbf{N}} = \bar{\mathbf{B}}\bar{\mathbf{S}} + \underline{\mathbf{N}}\end{aligned} \tag{15}$$

where $\bar{\mathbf{B}} = \mathbf{F}^{(1/2)}\mathbf{B}$ is the weighted steering vector after the reduced dimensional transformation, where $\mathbf{B} = [\mathbf{b}(\theta_1), \cdots, \mathbf{b}(\theta_P)]$ and $\mathbf{F} = \mathbf{G}^{\mathrm{H}}\mathbf{G} = \text{diag}\{[1, 2, \ldots, \underbrace{\min(\bar{M}, \bar{N}), \ldots, \min(\bar{M}, \bar{N})}_{|\bar{M}-\bar{N}|+1}, \ldots, 2, 1]\}$. Due to the fact that the reduced transformation matrix satifies $\mathbf{D}\mathbf{D}^{\mathrm{H}} = \mathbf{I}$, the noise matrix $\underline{\mathbf{N}} = \mathbf{D}\bar{\mathbf{N}}$ is also nonuniform noise. Then the covariance matrix is calculated by

$$\hat{\mathbf{R}} = \bar{\mathbf{Y}}\bar{\mathbf{Y}}^{\mathrm{H}}/J = \bar{\mathbf{B}}\hat{\mathbf{R}}_{\bar{S}}\bar{\mathbf{B}}^{\mathrm{H}} + \hat{\mathbf{R}}_{\underline{N}} \tag{16}$$

where $\hat{\mathbf{R}}_{\bar{S}} = \bar{\mathbf{S}}\bar{\mathbf{S}}^{\mathrm{H}}/J = \text{diag}([\sigma_1^2, \sigma_2^2, \cdots, \sigma_P^2])$ and $\hat{\mathbf{R}}_{\underline{N}} = \underline{\mathbf{N}}\underline{\mathbf{N}}^{\mathbf{H}}/J$. On the other hand, the sparse bayesian learning in [29] can be used to the received data in Eq.(16) for DOA estimation. However, this method needs the complex-valued processing procedure. It is well known that the computational burden of real-valued processing is only a quarter of those of complex-valued processing. Thus, the iteration of sparse bayesian learning strategy can be implemented in real-valued domain for reducing the computational burden, which is very useful for real-time operation in driving vehicle localization. It is noticed that the transmit-receive steering matrix $\bar{\mathbf{B}}$ satisfies

$$\mathbf{F}^{(1/2)}\mathbf{B}\Lambda = \Pi_{\bar{M}+\bar{N}-1}(\mathbf{F}^{(1/2)}\mathbf{B}\Lambda)^* \tag{17}$$

where $\Lambda = \text{diag}\{[e^{-j(\bar{M}+\bar{N}-2)/2\sin\theta_1}, e^{-j(\bar{M}+\bar{N}-2)/2\sin\theta_2}, \ldots, e^{-j(\bar{M}+\bar{N}-2)/2\sin\theta_P}]\}$ is a diagonal matrix. Thus, the received data can be transformation into real valued one by utilizing the unitary transformation [31]. Then unitary transformation matrix is given as

$$\mathbf{U}_{2k} = \frac{1}{\sqrt{2}}\begin{bmatrix}\mathbf{I}_k & j\mathbf{I}_k \\ \Pi_k & -j\Pi_k\end{bmatrix} \tag{18}$$

and

$$\mathbf{U}_{2k+1} = \frac{1}{\sqrt{2}}\begin{bmatrix}\mathbf{I}_k & 0 & j\mathbf{I}_k \\ \mathbf{0}^{\mathrm{T}} & \sqrt{2} & \mathbf{0}^{\mathrm{T}} \\ \Pi_k & 0 & -j\Pi_k\end{bmatrix}. \tag{19}$$

According to the principle of unitary transformation in [30], for a complex valued centro-Hermitian matrix $\Xi \in \mathbb{C}^{M\times N}$, $\mathbf{U}_M^{\mathrm{H}}\Xi\mathbf{U}_N$ is real valued. However, the estimated covariance matrix is Hermitian but generally not persymmetric due to the limited number of snapshots. Fortunately, the forward and backward (FB) spatial smoothing is applied for achieving the centrosymmetric covariance matrix, which is shown as

$$\bar{\mathbf{R}} = \frac{1}{2}(\hat{\mathbf{R}} + \Pi_{\bar{M}+\bar{N}-1}\hat{\mathbf{R}}^*\Pi_{\bar{M}+\bar{N}-1}) = \bar{\mathbf{B}}\bar{\mathbf{R}}_{\bar{S}}\bar{\mathbf{B}}^{\mathrm{H}} + \hat{\mathbf{R}}_{\underline{N}} \tag{20}$$

where $\bar{\mathbf{R}}_{\bar{S}} = \frac{1}{2}(\hat{\mathbf{R}}_{\bar{S}} + \Lambda\hat{\mathbf{R}}_{\bar{S}}^*\Lambda^{\mathbf{H}})$. The covariance matrix satisfies

$$\Pi_{M+N-1}\bar{\mathbf{R}}^*\Pi_{M+N-1} = \bar{\mathbf{R}} \tag{21}$$

According to Eq.(20), the number of snapshots is doubled after the FB spatial smoothing. Thus, the estimated accuracy of covariance matrix is improved and the covariance based SSR method can expect to achieve better performance. Then the real-valued covariance matrix is achieved as follows

$$\hat{\mathbf{R}}_{rv} = \mathbf{U}_{\bar{M}+\bar{N}-1}^{\mathrm{H}}\bar{\mathbf{R}}\mathbf{U}_{\bar{M}+\bar{N}-1} \tag{22}$$

According to the Eq.(17), the real-valued steering matrix is written as

$$\bar{\mathbf{B}}_{rv} = \mathbf{U}^{\mathbf{H}}\bar{\mathbf{B}}\Lambda \tag{23}$$

and the Eq.(22) is rewritten as

$$\hat{\mathbf{R}}_{rv} = \bar{\mathbf{B}}_{rv}\bar{\mathbf{R}}_{\bar{S}}\bar{\mathbf{B}}_{rv}^{H} + \bar{\mathbf{R}}_{\underline{N}} \tag{24}$$

Due to the fact that the covariance matrix is obtained from a finite number of snapshots, there exists an error between the estimated and idea covariance matrix. Then vectorizing the real valued covariance matrix without the nonuniform noise matrix, we have

$$\hat{\mathbf{g}} = \text{vec}(\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}}) = \mathbf{H}\mathbf{z} + \boldsymbol{\zeta} \tag{25}$$

where $\mathbf{H} = \bar{\mathbf{B}}_{rv}^{*} \odot \bar{\mathbf{B}}_{rv}$, and $\mathbf{z} = [\sigma_{s1}^2, \sigma_{s2}^2, \cdots, \sigma_{sP}^2]^{\mathrm{T}}$. $\boldsymbol{\zeta}$ is the estimated error, and it satisfies $\boldsymbol{\zeta} \sim \mathcal{CN}(0, \bar{\bar{Q}})$ with $\bar{\mathbf{Q}} = (\hat{\mathbf{R}}_{rv}^{\mathrm{T}} \otimes \hat{\mathbf{R}}_{rv})/J$ due to the orthogonal matrix $\mathbf{D}$ and $\mathbf{U}_{\bar{M}+\bar{N}-1}$ [31]. In order to carry out the SBL framework, the sparse data model must be established firstly. Discretize the spatial angle domain using a grid sampling $\Theta = [\bar{\theta}_1, \bar{\theta}_2, \cdots, \bar{\theta}_L]$, where $L \gg P$. Then the over complete dictionary $\bar{\mathbf{H}} = \bar{\mathbf{H}}(\Theta) = \bar{\mathbf{B}}_{rv}^{*}(\Theta) \odot \bar{\mathbf{B}}_{rv}(\Theta) = (\mathbf{U}^{\mathrm{H}}\mathbf{F}^{(1/2)}\mathbf{B}_{\bar{\theta}}^{*}\Lambda_{\bar{\theta}}^{*}) \odot (\mathbf{U}^{\mathrm{H}}\mathbf{F}^{(1/2)}\mathbf{B}_{\bar{\theta}}\Lambda_{\bar{\theta}})$ with $\mathbf{B}_{\bar{\theta}} = [\mathbf{b}(\bar{\theta}_1), \cdots, \mathbf{b}(\bar{\theta}_{\bar{L}})]$ and $\Lambda_{\bar{\theta}} = \mathrm{diag}\{[e^{-j(\bar{M}+\bar{N}-2)/2\sin\bar{\theta}_1}, \cdots, e^{-j(\bar{M}+\bar{N}-2)/2\sin\bar{\theta}_L}]\}$. Then the sparse model is expressed as follow

$$\hat{\mathbf{g}} = \bar{\mathbf{H}}\bar{\mathbf{z}} + \boldsymbol{\zeta} \tag{26}$$

where $\bar{\mathbf{z}}$ denotes a P sparse vector, where the nonzero elements of $\boldsymbol{\zeta}$ are corresponding to the desired DOAs. In order to implement the SBL technique, and following the basis ideal of SBL [29], Assuming that $\bar{\mathbf{z}} \sim \mathcal{CN}(\mathbf{0}, \Gamma)$, where $\Gamma = \mathrm{diag}(\boldsymbol{\gamma})$ with $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \cdots, \gamma_L]$. $\boldsymbol{\gamma}$ is a hyperparameter that controls the nonzero rows of $\bar{\mathbf{z}}$. When γ_i is zero, the corresponding row of $\boldsymbol{\gamma}$ becomes zero. Based on the Eq.(26), the likelihood function of $\hat{\mathbf{g}}$ can be derived as follows

$$\begin{aligned} p(\hat{\mathbf{g}}|\bar{\mathbf{z}}; \bar{\mathbf{Q}}) &= \mathcal{CN}(\hat{\mathbf{g}}|\bar{\mathbf{H}}\bar{\mathbf{z}}, \bar{\mathbf{Q}}) \\ &= |2\pi\bar{\mathbf{Q}}|^{-\frac{1}{2}}\exp\{-\frac{1}{2}[(\hat{\mathbf{g}}-\bar{\mathbf{H}}\bar{\mathbf{z}})^{\mathrm{T}}\bar{\mathbf{Q}}^{-1}(\hat{\mathbf{g}}-\bar{\mathbf{H}}\bar{\mathbf{z}})]\} \end{aligned} \tag{27}$$

Then using the Bayesian rule, the posterior distribution of $\bar{\mathbf{z}}$ is formulated as

$$\begin{aligned} p(\bar{\mathbf{z}}|\hat{\mathbf{g}}; \boldsymbol{\gamma}, \bar{\mathbf{Q}}) &= \frac{p(\hat{\mathbf{g}}|\bar{\mathbf{z}}; \bar{\mathbf{Q}})p(\bar{\mathbf{z}}|\boldsymbol{\gamma})}{\int p(\hat{\mathbf{g}}|\bar{\mathbf{z}}; \bar{\mathbf{Q}})p(\bar{\mathbf{z}}|\boldsymbol{\gamma})d\bar{\mathbf{z}}} \\ &= |2\pi\Sigma|^{-\frac{1}{2}}\exp\{-\frac{1}{2}[(\bar{\mathbf{z}}-\boldsymbol{\mu})^{\mathrm{H}}\Sigma^{-1}(\mathbf{z}-\boldsymbol{\mu})]\} \end{aligned} \tag{28}$$

where the mean $\boldsymbol{\mu}$ and covariance Σ are given by

$$\boldsymbol{\mu} = \Gamma\bar{\mathbf{H}}^{\mathrm{H}}(\bar{\mathbf{Q}} + \bar{\mathbf{H}}\Gamma\bar{\mathbf{H}}^{\mathrm{H}})^{-1}\hat{\mathbf{d}}_{rv} \tag{29}$$

$$\Sigma = \Gamma - \Gamma\bar{\mathbf{H}}^{\mathrm{H}}(\bar{\mathbf{Q}} + \bar{\mathbf{H}}\Gamma\bar{\mathbf{H}}^{\mathrm{H}})^{-1}\bar{\mathbf{H}}\Gamma \tag{30}$$

The hyperparameters $\boldsymbol{\gamma}$ in Eq.(29) and (30) is estimated by a type-II maximum likelihood, and the probability distribution of $\hat{\mathbf{g}}$ with respect to $\boldsymbol{\gamma}$ is the product of the likelihood function in Eq.(27) and the prior $p(\bar{\mathbf{z}}|\boldsymbol{\gamma})$ integrated over the real valued amplitudes $\bar{\mathbf{z}}$, which is shown as follows

$$\begin{aligned} p(\hat{\mathbf{g}}|\boldsymbol{\gamma}) &= \int p(\hat{\mathbf{g}}|\bar{\mathbf{z}}; \bar{\mathbf{Q}})p(\bar{\mathbf{z}}|\boldsymbol{\gamma})d\bar{\mathbf{z}} \\ &= |2\pi\Sigma_{\hat{\mathbf{g}}}|^{-\frac{1}{2}}\exp\{-\frac{1}{2}\hat{\mathbf{g}}^{\mathrm{H}}\Sigma_{\hat{\mathbf{g}}}^{-1}\hat{\mathbf{g}}\} \end{aligned} \tag{31}$$

where

$$\Sigma_{\hat{\mathbf{g}}} = \bar{\mathbf{Q}} + \bar{\mathbf{H}}\Gamma\bar{\mathbf{H}}^{\mathrm{H}} \tag{32}$$

In order to estimate the real-valued hyperparameters $\boldsymbol{\gamma}$, let the derivatives of the real-valued log-likelihood function of $p(\hat{\mathbf{g}}|\boldsymbol{\gamma})$ respect to $\boldsymbol{\gamma}$ be zero, i.e., $\partial\log(p(\hat{\mathbf{g}}|\boldsymbol{\gamma})|\boldsymbol{\gamma}))/\partial\boldsymbol{\gamma} = 0$. After some necessary mathematical operation, the updated rule of the hyperparameters $\boldsymbol{\gamma}$ is derived as follows

$$\gamma_i^{(q)} = \mu_i^{(q)}/\sqrt{\bar{\mathbf{h}}_i^{\mathrm{H}}(\Sigma_{\hat{\mathbf{g}}}^{(q)})^{-1}\bar{\mathbf{h}}_i} \tag{33}$$

where $\mu_i^{(q)}$is the ith entries of $\boldsymbol{\mu}$, and $\bar{\mathbf{h}}_i$ is the ith column of $\bar{\mathbf{H}}$. The corresponding posterior mean $\boldsymbol{\mu}^{(q)}$ and data covariance matrix $\Sigma_{\hat{\mathbf{g}}}^{(q)}$ are calculated in Eq.(29) and (32) for the qth iteration, respectably. Up to now, the hyperparameters $\boldsymbol{\gamma}$ is achieved by using the procedure of iteration. However, the variances of the nonuniform noise are also required to updated for calculating the covariance vector $\hat{\mathbf{g}}$ in Eq.(25). In our method, the least squares (LS) criterion is adopted to solve this issue [29]. In the SBL framework, the parameters are updated in each interaction. Thus, P "active" DOAs $\hat{\theta}_p(p = 1, 2, \cdots, P)$ are from the spatial spectrum of hyperparameters $\boldsymbol{\gamma}$. Then the corresponding real-valued active steering matrix is constructed as $\mathbf{D}_P = \mathbf{U}_{\bar{M}+\bar{N}-1}^{H}\mathbf{F}^{(1/2)}\mathbf{B}_P\Lambda_P$ with $\mathbf{B}_P = [\mathbf{b}(\hat{\theta}_p), \cdots, \mathbf{b}(\hat{\theta}_P)]$ and $\Lambda_P = \mathrm{diag}\{[e^{-j(\bar{M}+\bar{N}-2)/2\sin\hat{\theta}_1}, [e^{-j(\bar{M}+\bar{N}-2)/2\sin\hat{\theta}_2}, \cdots, e^{-j(\bar{M}+\bar{N}-2)/2\sin\hat{\theta}_P}]\}$. Based on the basis idea of subspace technique, for the uncorrected sources, the columns of $\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}}$ and $\mathbf{D}_P$ can span the same subspace, which indicates that there exists a linear relationship between $\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}}$ and $\mathbf{D}_P$, shown as $\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}} = \mathbf{D}_P\mathbf{T}$, where $\mathbf{T}$ is a full-rank matrix. Then the $\bar{k}(\bar{k} = 1, 2, \cdots, M+N-1)$ columns of $\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}}$ is written as $\mathbf{c}_{\bar{k}} = \mathbf{v}_{\bar{k}} - \bar{\sigma}_1^2\mathbf{e}_{\bar{k}}$, and $\bar{\sigma}_{\bar{k}}^2$ denotes the kth variance of nonuniform noise, where $\mathbf{e}_{\bar{k}}$ denotes a column vector of all zeros except a 1 in the $\bar{k}$th position. Thus, the estimated error between $\bar{k}$th column of $\hat{\mathbf{R}}_{rv} - \bar{\mathbf{R}}_{\underline{N}}$ and $\mathbf{D}_P\mathbf{T}$ can be shown as

$$\varepsilon(\bar{k}) = ||\mathbf{c}_{\bar{k}} - \mathbf{D}_P\mathbf{t}_{\bar{k}}||_2^2 \tag{34}$$

where $\mathbf{t}_{\bar{k}}$ denotes the $\bar{k}$th column of the full-rank matrix $\mathbf{T}$. Applying the least squares (LS) criterion to Eq.(34), we have $\mathbf{t}_{\bar{k}} = (\mathbf{D}_P^{\mathrm{H}}\mathbf{D}_P)^{-1}\mathbf{D}_P^{\mathrm{H}}\mathbf{c}_{\bar{k}}$. Substituting $\mathbf{t}_{\bar{k}}$ into Eq.(34) yields

$$\Im(\bar{\sigma}_{\bar{k}}^2) = \sum_{\bar{k}=1}^{\bar{M}+\bar{N}-1} ||\mathbf{c}_{\bar{k}} - \mathbf{D}_P\mathbf{t}_{\bar{k}}||_2^2 = \sum_{\bar{k}=1}^{\bar{M}+\bar{N}-1} \mathbf{c}_{\bar{k}}^{\mathrm{H}}\Xi\mathbf{c}_{\bar{k}} \tag{35}$$

where $\Xi = \mathbf{I}_{\bar{M}+\bar{N}-1} - \mathbf{D}_P(\mathbf{D}_P^{\mathrm{H}}\mathbf{D}_P)^{-1}\mathbf{D}_P^{\mathrm{H}}$. Then the updated rule of the variances of nonuniform noise can be achieved by the derivation as $\partial\Im(\bar{\sigma}_{\bar{k}}^2)/\partial\bar{\sigma}_{\bar{k}}^2 = 0$, and we have

$$\bar{\sigma}_{\bar{k}}^2 = \frac{\mathbf{e}_{\bar{k}}^{\mathrm{T}}\Xi\mathbf{v}_{\bar{k}} - \mathbf{v}_{\bar{k}}^{\mathrm{H}}\Xi\mathbf{e}_{\bar{k}}}{2\mathbf{e}_{\bar{k}}^{\mathrm{T}}\Xi\mathbf{v}_{\bar{k}}}. \tag{36}$$

Up to now, both the parameters and the variances of the nonuniform noise are updated by the proposed method. Then the hyperparameter $\boldsymbol{\gamma}$ is obtained when the procedure of iteration is convergent, then the DOA is achieved by plotting the spatial spectrum of $\boldsymbol{\gamma}$. The convergence conidtion is set as $||\boldsymbol{\gamma}^{(q+1)} - \boldsymbol{\gamma}^{(q)}||_2/||\boldsymbol{\gamma}^{(q)}||_2 < \zeta$, where ζ denotes the threshold of conversance. In summary, the proposed robust unitary SBL for DOA estimation in the presence of unknown mutual coupling and nonuniform noise is given in **algorithm1**.

Algorithm 1 Robust Sparse Bayesian Learning Scheme

Input: The received data $\mathbf{X}$;
Initialization: $\bar{\mathbf{H}}$, $\bar{\mathbf{Q}}$, $\bar{\mathbf{R}}_{\underline{N}}$, $\boldsymbol{\gamma}^{(0)}$;
Robust sparse Bayesian learning
Achieve $\bar{\mathbf{X}}$ by Eq.(5) and Eq.(9), and estimate $\hat{\mathbf{R}}$ by Eq.(16);
Estimate the real valued covariance matrix $\bar{\mathbf{B}}_{rv}$ by Eq.(20) and (22).
Achieve the real valued covariance vector $\hat{\mathbf{g}}$ without the influence of nonuniform noise by Eq.(25);
while $\sim$ Converge **do**
  Update $\boldsymbol{\mu}$ by Eq.(29);
  Update $\Sigma_{\hat{\mathbf{g}}}$ by Eq.(32);
  Update $\boldsymbol{\gamma}$ by Eq.(33);
  Update $\bar{\sigma}_{\bar{k}}^2$ by Eq.(36)
end while
Output: $\bar{\mu}$, $\bar{\boldsymbol{\gamma}}$.

IV. RELATED REMARKS

Remark 1: In the proposed method, the real-valued covariance matrix is involved the FB spatial smoothing. The number of snapshots is doubled in the received data, which indicates that the covariance matrix is estimated more correctly. One the other hand, the proposed method can eliminate the mutual coupling effect, and the variances of nonuniform noise are updated in SBL framework. Therefore, the proposed method is expected to have superior performance than existing SSR based methods, which indicates that the performance of vehicle localization is improved remarkably.

Remark 2: According to the implementation of the proposed method, the covariance vector is required to estimated effectively. In order to achieve this purpose, the covariance matrix should be a full rank matrix, which indicates that the number of snapshots should satisfy $J \geq \bar{M} + \bar{N} - 1$.

Remark 3: To further reduce the computational burden and the modeling error of spatial sampling grids, a refined procedure is utilized to achieve this purpose [32], [33]. The 1-D spatial searching is formulated to estimate the DOA, which only requires P clusters searching, and it can be expressed as

$$\mathfrak{L}(\hat{\theta}) = \underset{\theta\in\nabla_p}{\operatorname{argmax}} |\bar{\mathbf{h}}^{\mathrm{T}}(\theta)\bar{\Sigma}_{-p}^{-1}[\bar{\mathbf{h}}(\theta)\bar{\mathbf{h}}^{\mathrm{H}}(\theta)\Sigma_{-p}^{-1}\hat{\mathbf{g}}\hat{\mathbf{g}}^{\mathrm{T}} - \hat{\mathbf{g}}\hat{\mathbf{g}}^{\mathrm{T}}\Sigma_{-p}^{-1}\bar{\mathbf{h}}(\theta)\mathbf{h}^{\mathrm{H}}(\theta)]\Sigma_{-p}^{-1}\frac{\partial\bar{\mathbf{h}}(\theta)}{\partial\theta}|^{-1} \quad (37)$$

where $\bar{\mathbf{h}}(\theta) = (\mathbf{U}^{\mathrm{H}}\mathbf{F}^{(1/2)}\mathbf{b}^{*}e^{j(\bar{M}+\bar{N}-2)/2\sin\theta}) \odot (\mathbf{U}^{\mathrm{H}}\mathbf{F}^{(1/2)}\mathbf{b}e^{-j(\bar{M}+\bar{N}-2)/2\sin\theta})$. and $\Sigma_{-p} = \bar{\mathbf{Q}} + \bar{\mathbf{H}}_{-p}\Gamma_{-p}\bar{\mathbf{H}}_{-p}^{\mathrm{H}}$, where $\bar{\mathbf{H}}_{-p}$ is a real-valued matrix which is achieved by canceling one column of $\bar{\mathbf{H}}$ corresponding to θ_p. Γ_{-p} equals Γ by canceling its rows and columns corresponding to θ_p. ∇_p is the peak rang of the pth source, and the DOAs are obtained from the spatial spectrum $\mathfrak{L}(\hat{\theta})$.

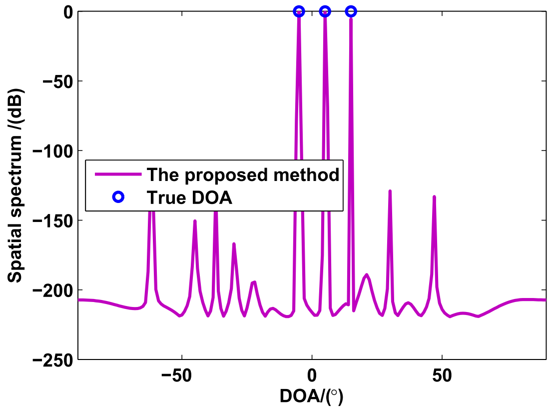

FIGURE 3. The spatial spectrum of the proposed method (SNR= 0*dB*, $J = 200$).

V. SIMULATION RESULTS

In this section, The simulation results about the proposed method for DOA estimation in MIMO radar system is given, which is used to verify the performance. The proposed method is compared with the l_1-SVD based algorithm in [26] and the SBL based algorithm in [29]. a MIMO radar consisting with $M = 8$ transmit antennas and $N = 10$ receive antennas is used, and the uniform linear arrays (ULAs) with half-wavelength spacing is used for the transmit and receive arrays. Unless otherwise stated in the following simulation results, the number of targets is assumed to be known firstly, and we consider $P = 3$ uncorrelated targets with the DOAs of $\theta_1 = -5^\circ$, $\theta_2 = 5^\circ$ and $\theta_3 = 15^\circ$, and they satisfie the condition of far field. The nonuniform noise $\mathbf{R}_{\bar{\mathbf{n}}} = \mathrm{diag}\{[10, 1, 9, 7, 2, 6, 1.5, 1, 3, 0.5]\}$. The worst noise power ratio (WNPR) is defined as follows

$$\mathrm{WNPR} = \sigma_{max}^2/\sigma_{min}^2 \quad (38)$$

where σ_{max}^2 and σ_{min}^2 are the maximum and minimum nonuniform noise variances, respectively. The root mean squared error (RMSE) for evaluating the performance is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\ell P}\sum_{i=1}^{\ell}\sum_{p=1}^{P}(\theta_p - \theta_{p,i})} \quad (39)$$

where $\theta_{p,i}$ is the estimated value of the pth source at the ith trial, and ℓ is number of Monte Carlo trials and set as $\ell = 200$. The spatial grid is 0.1° discretizing from -90° to 90°. The initialization parameters of the proposed method are set as $\hat{\mathbf{g}}^{(0)} = \mathrm{vec}(\hat{\mathbf{R}}_{rv} - \mathbf{I}_{M+N-1})$ and $\boldsymbol{\gamma}^{(0)} = \bar{\bar{\mathbf{H}}}^{\mathrm{H}}(\bar{\mathbf{H}}\bar{\mathbf{H}}^{\mathrm{H}})^{-1}\hat{\mathbf{g}}^{(0)}$.

Fig.3 shows the spectrum of the proposed method, where the SNR=0dB and $J = 200$. The the nonzero mutual coefficients are $\mathbf{c}_t = [1, 0.4174+j0.0577]$ and $\mathbf{c}_r = [1, -0.5121-j0.1029]$, respectively. From Fig.3, it can be seen that there exists 3 sharp peaks corresponding to the true DOAs, which verifies that the proposed method is work well in the mutual coupling and nonuniform noise, which indicates that the position of vehicle is correctly achieved by using cross localization based on the estimated DOAs.

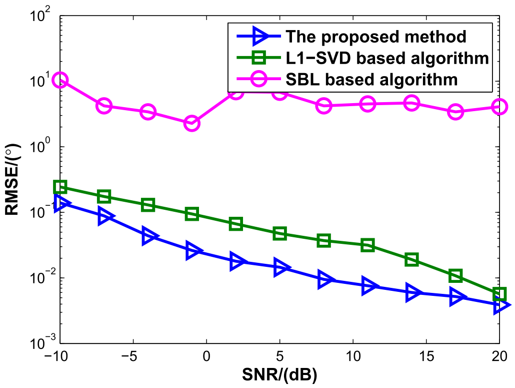

FIGURE 4. The RMSE versus SNR with different methods.

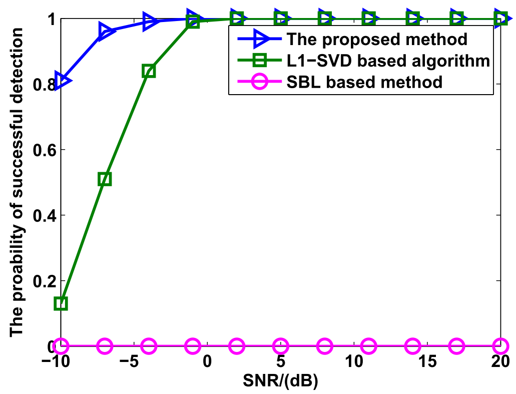

FIGURE 5. The probability of successful detection versus SNR ($J = 200$).

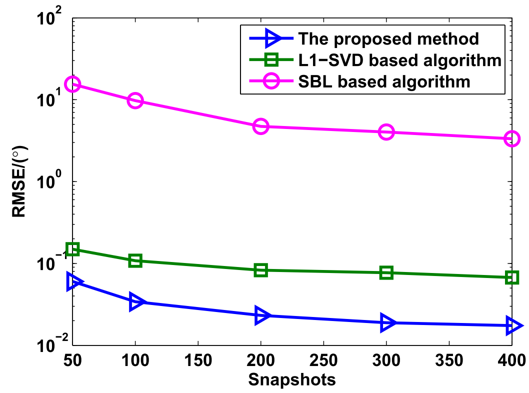

FIGURE 6. RMSE versus snapshots for different methods (SNR=0dB).

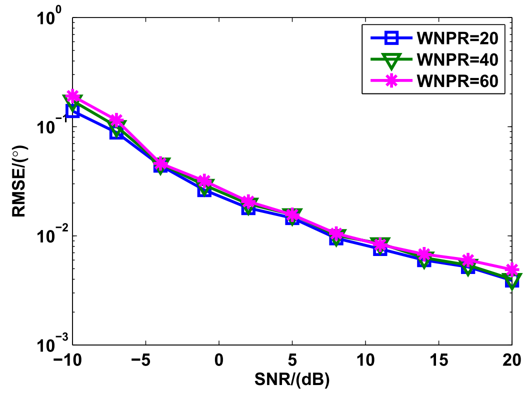

FIGURE 7. The RMSE versus SNR with different WNPR ($J = 200$).

Fig.4 depicts the RMSE versus SNR for the proposed method, l_1-SVD based algorithm and SBL based algorithm, where the number of snapshots is set as $J = 200$, and the nonzero mutual coefficients are $\mathbf{c}_t = [1, 0.2174 + j0.0577]$ and $\mathbf{c}_r = [1, 0.1121 - j0.1029]$, respectively. According to the Fig.4, it can be seen that the SBL based algorithm fails to work due the influence of mutual coupling. Furthermore, the proposed method achieves superior performance than l_1-SVD based algorithm. This is because that proposed can update the variances of nonuniform noise for eliminating its effect, but the l_1-SVD based algorithm does not have this ability. Thus, the proposed method can achieve the best performance due to its advantages.

Fig.5 depicts detection performance of DOA estimation versus SNR for the proposed method, l_1 based algorithm and SBL based algorithm, where the number of snapshots is set as $J = 100$, and the nonzero mutual coefficients are set as $\mathbf{c}_t = [1, 0.2174 + j0.0577]$ and $\mathbf{c}_r = [1, 0.1121 - j0.1029]$, respectively. In this simulation, the successful detection of all sources is defined as if the estimation error of all DOAs satisfies $max_{i=1,2,3}|\hat{\theta}_i - \theta_i| \leq 0.2°$, where $\hat{\theta}_i$ is the estimated value of θ_i. As seen in Fig.5, it is clearly observed that when the SNR is high enough, the proposed method and the l_1-SVD based algorithm exhibit 100% detection performance. But the SBL based method achieve 0% detection performance in all SNR region due to the fact that it fails to work. On the other hand, for each algorithm, the probability of successful detection begins dropping at one point of the SNR, and this point is named as SNR threshold. According to Fig.5, the proposed method achieves higher SNR threshold than l_1-SVD based algorithm. This is because that the proposed method has the ability of nonuniform noise suppression.

Fig.6 shows the RMSE versus snapshots for for the proposed method, l_1 based algorithm and SBL based algorithm, where the SNR is set as SNR=0 dB, and the nonzero mutual coefficients are $\mathbf{c}_t = [1, 0.2174 + j0.0577]$ and $\mathbf{c}_r = [1, 0.1121 - j0.1029]$, respectively. As shown in Fig.6, with the increasing number of snapshots, all the methods except for the SBL based algorithm achieve better angle estimation performance. The proposed method provides superior performance than l_1-SVD based algorithm due to the accurate estimated covariance matrix with large number of snapshots.

Fig.7 depicts the RMSE of the proposed method with different WNPR, where the number of snapshots is set as $J = 200$. The nonzero mutual coefficients are $\mathbf{c}_t = [1, 0.2174 + j0.0577]$ and $\mathbf{c}_r = [1, 0.1121 - j0.1029]$, respectively. As shown in Fig.7, the RMSE of the proposed method becomes larger with the same SNR when the WNPR is increased, but its performance is also reasonable, which indicates that the proposed method is robust with the different WNPR. The main reason is that the proposed method can update the variances of nonuniform noise in the unitary SBL iterations.

VI. CONCLUSION

In this paper, we have proposed a robust DOA estimation approach based unitary sparse bayesian learning for vehicle localization with two cooperation MIMO radars. Under the unknown mutual coupling and nonuniform noise in MIMO system, the proposed method uses a linear transformation to eliminate the mutual coupling effect and achieves the real-valued covariance vector by using unitary transformation. Then a robust unitary SBL procedure is proposed for DOA estimation with the updating of nonuniform noise via LS strategy. The simulation results are used to demonstrate that the proposed method not only works well in the presence of unknown mutual coupling and nonuniform noise, but also achieves superior performance than the existing SSR based algorithms. In addition, the proposed method only needs the real-valued processing, which is very useful for real-time vehicle localization.

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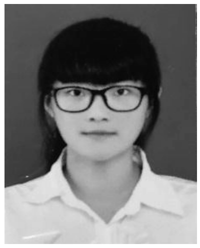

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