Two Novel DOA Estimation Approaches for Real-Time Assistant Calibration Systems in Future Vehicle Industrial

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Abstract—Intelligent transportation systems (ITSs) of industrial systems have played an important role in Internet of things (IOT). The assistant calibration system (ACS) of vehicles is an emerging technology, which services the driver to drive the vehicle safely. To solve some existing problems in ACS such as frequency pairing, vehicle localization judgment, and driving in the curve road, two direction-of-arrival (DOA) estimation-based approaches are proposed to resolve these problems. However, the performance of most conventional DOA estimation algorithms is affected by the mutual coupling among the elements. The special structure of the mutual coupling matrix of the uniform linear array is applied to eliminate the effect of mutual coupling. Then, a novel on-grid DOA estimation algorithm based on compressive sensing (CS) strategies is proposed in the presence of unknown mutual coupling. In order to compensate the aperture loss of discarding information that the array receives, the array aperture is extended by the vectorization operator. In order to deal with the effect of grid mismatch, an off-grid DOA estimation algorithm based on sparse Bayesian learning (SBL) is proposed in this paper. The temporal correlation between the neighboring snapshot numbers is considered in the off-grid algorithm. The computer simulation verifies the effectiveness of the proposed algorithms.

Index Terms—Compressive sensing (CS), direction-of-arrival (DOA) estimation, intelligent transportation systems (ITSs), sparse Bayesian learning (SBL).

I. INTRODUCTION

Recent advances in radio, network, and cloud computation technologies have supported the development of the Internet of things (IOT) services and products [1]. IOT aims at connecting various physical and digital devices to the Internet in order to improve the quality of service for people [2], [3]. As an emerging technology, IOT has many applications in existing industrial systems such as transportation systems and manufacturing systems [4]. Today, researchers connect IOT with more technologies such as sensors, GPS devices, and mobile devices. Intelligent transportation systems (ITS) have played an important role in IOT, which have emerged as an effective way of improving the performance of transportation systems and enhancing travel security [5]. When people drive the vehicle, some sight blind areas may exist because the driver cannot observe all of the things through the rearview mirrors. If the obstacles including the speeding vehicle, roadblock, etc., exist at the surroundings of the vehicle, the driver’s life would get into a dangerous situation. Thus, the assistant calibration system (ACS) for vehicles is introduced, which has been used in adaptive cruise control systems in vehicles [6]. The radar system is an important part in ACS, which can detect multiple targets simultaneously. However, this makes it difficult to distinguish between two targets with different frequencies in a period radar echoes. The details will be illustrated in Section II. Thus, the parameter pairing problem for frequencies has to be solved. It can be known that the angle informations of two targets are different. Thus, the direction-of-arrival (DOA) estimation is introduced as an assistant method to solve this problem. In addition, when the vehicle is turning a corner, the DOAs of objects are also important information to help the drivers distinguish other vehicles, streetlight, and billboard.

DOA estimation is a major part of array signal processing which is applied in various areas such as smart antennas, wireless communication systems, radar, sonar, and seismology [7]–[9]. At present, DOA estimation algorithms can be divided into two categories: subspace-based algorithms and parameter estimation algorithms. The first group is based on the decomposition of covariance matrix such as the multiple signal classification (MUSIC) [10] and estimation of signal parameters via rotational invariance techniques (ESPRIT) [11]. The second group includes the deterministic maximum likelihood (DML) and stochastic maximum likelihood (SML) [7] algorithms, which have excellent DOA estimation performance. However, they require accurate initialization to guarantee the convergence of the algorithms and suffer from high computational complexity. All of these algorithms depend on the second-order statistic properties of the data. In other words, they need a large number of snapshots to estimate DOA accurately. However, if the sources are strongly correlated or coherent or when only a small number of snapshots can be used, the performance of these algorithms will deteriorate significantly due to the rank deficiency of the covariance matrix.
Recently, DOA estimation has attracted a lot of attention by the application of sparse signal representation and compressive sensing (CS). A recursive weighted minimum norm algorithm called FOCUSS was applied to DOA estimation [12]. The well-known sparse recovery algorithm for DOA estimation is called \( l_1 \) - SVD, and the singular value decomposition (SVD) made the computational complexity much lower [13]. An alternative strategy called joint \( l_0 \) approximation (JLZA) DOA estimation was proposed by recovering a joint-sparse signal from multiple measurement vectors (MMVs) [14]. A sparse covariance-based estimation method (SPICE) was proposed for DOA estimation with covariance fitting [15]–[17]. A sparse representation of array covariance vectors was proposed, in which DOA estimation was achieved by jointly finding the sparsest coefficients of the array covariance vectors in an overcomplete basis [18]. The DOA estimation method for sparse array was proposed by recovering a sparse signal reconstruction [19]. The covariance matrix sparse representation algorithm was proposed for estimating DOA of both narrowband and wideband signals [20], [21]. The sparse Bayesian learning (SBL) was applied to estimate DOA as an efficient ML method [22]. Furthermore, the DOA estimation based on spatial CS was proposed [23], [24], and the inherent bias was mitigated via expected likelihood [25]. The Bayesian CS was also used for DOA estimation [26].

The aforementioned described methods exhibit a number of advantages over the conventional methods, including increased resolution, limited number of snapshots, and correlation of signals. However, under imperfect conditions such as unknown mutual coupling or inconsistent gain and phase, the performance of these algorithms deteriorates significantly. Many algorithms have been proposed to deal with mutual coupling effects [27]–[30]. Without prior information of the array manifold, the eigenstructure-based method proposed in [27] can calibrate the array parameters including the mutual coupling.

A novel online mutual coupling compensation algorithm was proposed for uniform linear array (ULA), and the estimated calibration matrix can be embedded within any classical super-resolution direction-finding method [28]. Without the spectrum peak search and iteration, a generalized eigenvalues utilizing signal subspace eigenvectors (GESEE) algorithm for ULA was proposed to eliminate the effect of mutual coupling [29]. There is little literature to consider the effect of mutual coupling in multipath environment. Based on the special structure of the mutual coupling matrix (MCM) for ULA, the effect of mutual coupling was eliminated in the condition of coherent signals [30]. The source location problem in wireless sensor networks is discussed in [31].

In this paper, in order to solve some existing problems in ACS such as frequency pairing, vehicle localization judgment, and driving in the curve road in ITS, two novel DOA estimation algorithms are proposed in the presence of unknown mutual coupling. The special structure of MCM of ULA is applied to eliminate the effect of mutual coupling. For the on-grid DOA estimation algorithm, in order to compensate the aperture loss of discarding information that the array receives, the array aperture is extended by the vectorization operator. For the off-grid DOA estimation algorithm, the SBL algorithm is applied, which avoids the grid mismatch of the on-grid DOA estimation algorithm. The computer simulation verifies the effectiveness of the proposed algorithms.

The rest of this paper is organized as follows. Section II introduces the existing problems in ACS. Section III constructs the system architecture of ACS. Section IV introduces the snapshot data model and describes the MUSIC with the unknown mutual coupling. Section V proposes the on-grid DOA estimation algorithm. Section VI proposes the off-grid DOA estimation algorithm. Section VII discusses some issues about the proposed algorithms. Section VIII presents the simulation results. Section IX summarizes our conclusion.

II. PROBLEM FORMULATION

Frequency-modulated continuous wave (FMCW) is one basic LFM waveform for vehicle radars. As shown in Fig. 1, there is only one radar echo. \( f_t \) is the emission frequency for the transmitter, and its average frequency is \( f_{0t} \); the various period of \( f_{0t} \) is \( T_m \), and \( T_m \) is usually several hundreds of a second. \( f_r \) is the echo frequency that comes from the target reflection. It has the same change regulation as the emission frequency, but the time is delayed \( t_R \). The maximum frequency deviation of emission frequency modulation is \( \pm \Delta f \). \( f_b \) is the beat frequency between the emissive and receptive signals, and its average value is defined as \( f_{\text{ave}} \).

As shown in Fig. 1, the emission frequency \( f_t \) and the echo frequency \( f_r \) are, respectively, expressed as

\[
 f_t = f_0 + \frac{df}{dt} t + f_0 + \frac{\Delta f}{T_m/4} t 
\]

\[
 f_r = f_0 + \frac{\Delta f}{T_m/4} \left( t - \frac{2R}{c} \right).
\]

The beat frequency \( f_b \) is

\[
 f_b = f_t - f_r = \frac{8\Delta f R}{T_m c}. 
\]

For a target echo with distance \( R \), the average beat frequency value \( f_{\text{ave}} \) in a measuring period can be expressed as

\[
 f_{\text{ave}} = \frac{8\Delta f R}{T_m c} \left( \frac{T_m - \frac{2R}{c}}{T_m} \right).
\]
Thus, the relationship $T_m \gg 2R/c$ is usually satisfied, and then, the target distance $R$ is given by

$$R = \frac{c}{8\Delta f} \frac{f_{bav}}{f_m}$$  

(5)

where $f_m = 1/T_m$ is the modulation frequency.

When the target is moving with distance $R$ and radial velocity $v$, the echo frequency $f_r$ is expressed as

$$f_r = f_b + f_d \pm \frac{\Delta f}{T_m/4} \left( t - \frac{2R}{c} \right)$$  

(6)

where $f_d$ is the Doppler frequency and the positive and negative signs stand for the gradient before and after signal modulation, respectively. When $f_d < f_{bav}$, the beat frequencies are expressed as

$$f_{b+} = f_t - f_r = \frac{8\Delta f}{T_m/4} R - f_d$$  

(7)

$$f_{b-} = f_r - f_t = \frac{8\Delta f}{T_m/4} R + f_d.$$  

(8)

Then, the distance $R$ and radial velocity $v$ are expressed as

$$R = \frac{c}{8\Delta f} \frac{f_{b+} + f_{b-}}{2f_m}$$  

(9)

$$v = \frac{\lambda}{4} (f_{b+} + f_{b-}).$$  

(10)

The actual condition is that the radar may receive multiple target echoes in a very short time. The difficulty is how to distinguish the target echoes of positive and negative gradients generated by the identical target. It can be seen from Fig. 1 that, if there are $K$ target echoes before $t_3$ and there are $K$ target echoes after $t_3$ as well, there would be $K^2$ combinations. In fact, there are only $K$ combinations, and other $K^2 - K$ combinations are false pairings. However, the identical target echoes before and after $t_3$ have the same angle information. This is an important parameter, which can be regarded as a basis for the different frequency pairings.

As shown in Fig. 2, when the target distance (i.e., the distance between two vehicles) detected by the radar is closed in the identical roadway, the alert should ring out in order to warn the driver. However, if the vehicle is driven in the neighboring roadway, the alert should not ring out. Thus, the DOA of the target can give us enough information to judge the location of the vehicle. In addition, the guardrail on the roadway can also be detected by the continuous angle information, which cannot be regarded as the false alarm. As shown in Fig. 3, when the vehicle is driven in a curve road, it is important to judge the vehicle whether in the identical or neighboring roadway by the angle information. The billboards at the road side can also be detected by their angle information received by the radar of the vehicle.

III. ACS

In this section, the ACS of the vehicle containing the multiple targets direction finding system is constructed. As shown in Fig. 4, this system contains two modules. One is the signal-processing module, and the other is the system fusion and decision-making module. The signal-processing module includes the steering wheel control module, infrared imaging module, and millimeter-wave radar module. The function of the steering wheel control module is to obtain the corner angle, throttle, and brake value of the steering wheel. The function of the infrared imaging module is to obtain the distance, position, and speed of the obstacle in front of someone’s vehicle. The millimeter-wave radar module is used to obtain the distance, position, and speed of the vehicles, fence, billboards, and other obstacles in front of someone’s vehicle. The system fusion and decision-making module includes the bus controller and drivers I and II, infrared image processing and display controlling unit,
liquid crystal display (LCD) embedded in the vehicle, computer embedded in the vehicle, and sound and light alarm system.

The data collected by the steering wheel control module, infrared imaging module, and millimeter-wave radar module are processed in the signal-processing module, and then, the various parameter information of the vehicle in the motion state can be obtained. The parameter information of the signal-processing module (the infrared imaging and millimeter-wave radar modules are the most important providers of the information) is fused based on the system fusion and decision-making module. One way of the processed information is delivered to the infrared image processing and display controlling unit via the bus controller and driver I. The delivered parameter is analyzed and fused deeply in this module. The location of the vehicle and its surroundings are shown on the vehicle LCD. The other way of the processed information is delivered to a small embedded computer via the bus controller and driver II. Based on the analysis of the computer, the sound and light alarm system is triggered. The alarm of the rear end, rollover, and route departure is controlled by this system. The result of the alarm is displayed in the LCD.

As mentioned previously, we can know that the millimeter-wave radar module plays a very important role for the ACS. The accurate DOA estimation of targets in the millimeter-wave radar module is one of the most important functions which provide the angular information of the obstacles.

IV. CONVENTIONAL MUSIC ALGORITHM CONSIDERING UNKNOWN MUTUAL COUPLING

In this section, the conventional DOA estimation algorithm based on the MUSIC algorithm in the presence of unknown mutual coupling is introduced.

Consider a scenario of $K$ uncorrelated narrowband far-field signals impinging on an $M$-element ($M > K$) ULA. The distance between adjacent elements is $d$. The $K$ signals $s_1(t), s_2(t), \ldots, s_K(t)$ arrive at the array from different directions $\theta_1, \theta_2, \ldots, \theta_K$, where $\theta_k$ denotes the location parameter of the $k$th signal. The array output of $N$ snapshots can be represented as

$$X(t) = A(\theta)S(t) + N(t), \quad t = 1, \ldots, N \tag{11}$$

where $X(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T$ is the $M \times 1$ array output vector, $S(t) = [s_1(t), s_2(t), \ldots, s_K(t)]^T$ is the signal vector, $N(t) = [n_1(t), n_2(t), \ldots, n_M(t)]^T$ is the additive circular complex Gaussian white noise vector whose elements are normally distributed with zero-mean and variance $\sigma^2$

$$E\{N(t)N^H(t)\} = 0, E\{N(t)N^H(t)\} = \sigma^2I. \tag{12}$$

$(\cdot)^T$ and $(\cdot)^H$ are the transpose and conjugate transpose, respectively. $E\{\cdot\}$ is the mathematical expectation. $0$ and $I$ are the $M \times M$ zero matrix and $M \times M$ identity matrix, respectively. $A(\theta) = [\alpha(\theta_1), \alpha(\theta_2), \ldots, \alpha(\theta_K)]$ is the manifold matrix with steering vector $\alpha(\theta_k) = [1, v_{k1}, \ldots, v_{kM-1}]^T$, where $v_k = \exp(-j2\pi d \sin(\theta_k)/\lambda)$ is the steering vector of the $k$th signal.

The $M \times M$ array covariance matrix without taking into account the mutual coupling is given by

$$R = E\{X(t)X^H(t)\} = A(\theta)R_S A^H(\theta) + \sigma^2I \tag{13}$$

where $R_S = E\{S(t)S^H(t)\}$ is the signal power matrix.

When the effect of mutual coupling is taken into consideration, the correctional array covariance matrix of the array output is given by

$$R_{MC} = CA(\theta)R_S A^H(\theta)C^H + \sigma^2I \tag{14}$$
where $C$ is the MCM of the array. Generally, the mutual coupling effect between elements is in inverse proportion to the distance between the elements. According to the reciprocity principle, the MCM is a symmetrical matrix.

For the ULA, $d < \lambda/2$, where $\lambda$ is the signal wavelength. The mutual coupling degree of freedom is assumed to be $p$. When the distance between two elements is larger than $(p-1)d$, the mutual coupling coefficient attenuates to zero. Thus, the MCM $\tilde{C}$ is obtained by the EVD of the distance between the elements. According to the reciprocity function, which can be described as follows:

The $K$-dimensional subspace is the MCM of the array. Generally, the mutual coupling is $\tilde{C}$, and the space of $\tilde{c}_{\cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot}$ satisfies

$$\mathbf{C} = \text{Toeplitz}(c)$$

$$= \text{Toeplitz} \left\{ \{c_1, c_2, \ldots, c_p, 0, \ldots, 0\} \right\}$$

$$= \begin{bmatrix}
1 & c_1 & \cdots & c_p & \cdots & 0 \\
\vdots & 1 & \cdots & \cdots & \cdots & 0 \\
c_p & \cdots & \cdots & \cdots & \cdots & c_1 \\
0 & \cdots & \cdots & \cdots & \cdots & c_1 \\
0 & \cdots & \cdots & \cdots & \cdots & c_1 \\
\end{bmatrix}. \quad (15)$$

The eigenvalue decomposition (EVD) of the exact covariance matrix $\mathbf{R}_{MC}$ is expressed as

$$\mathbf{R}_{MC} = \mathbf{U}_S \Sigma_S \mathbf{U}_S^H + \mathbf{U}_N \Sigma_N \mathbf{U}_N^H \quad (16)$$

where $\mathbf{U}_S$ and $\mathbf{U}_N$ are the signal subspace and noise subspace corresponding to $K$ larger eigenvalues and $M-K$ smaller eigenvalues, respectively.

In practice, the sampling data are finite; thus, the array covariance matrix can be estimated by

$$\tilde{\mathbf{R}}_{MC} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{X}(t)\mathbf{X}^H(t) \quad (17)$$

where $\tilde{N}$ stands for snapshot number. Then, $\tilde{\mathbf{U}}_S$ and $\tilde{\mathbf{U}}_N$ are obtained by the EVD of $\tilde{\mathbf{R}}_{MC}$. The mutual coupling is assumed to be known as a priori, and the space of $\langle \mathbf{c}_{a}(\theta_1), \mathbf{c}_{a}(\theta_2), \ldots, \mathbf{c}_{a}(\theta_K) \rangle$ is identical with the signal subspace $\mathbf{U}_S$. Meanwhile, it is orthogonal to the noise subspace $\mathbf{U}_N$ which is expressed as follows:

$$\| \tilde{\mathbf{U}}_N^H \mathbf{c}_{a}(\theta_k) \| = 0, \quad i = 1, 2, \ldots, K. \quad (18)$$

The $\| \cdot \|$ is defined as the Frobenius norm. The conventional MUSIC algorithm involves constructing the spatial-spectrum function, which can be described as follows:

$$\mathbf{P}(\theta) = \frac{1}{\| \tilde{\mathbf{U}}_N^H \mathbf{c}_{a}(\theta_k) \|^2}. \quad (19)$$

However, in many situations, the mutual coefficient is not known; thus, the approach mentioned previously cannot be used. In addition, most of the state-of-the-art approaches are not appropriate for DOA estimation with unknown mutual coupling. Therefore, a novel algorithm is proposed in order to solve this problem.

V. ON-GRID DOA ESTIMATION

A. DOA Estimation Through Spatial CS

This section summarizes the DOA estimation approach based on the CS framework, which is inseparable from the MMV problem [32]–[35]. The CS framework exploits the spatial sparsity to discretize the bearing space into a large number of distinct directions, where only a few of them possess high power, i.e., the DOAs of the impinging signal are assumed to belong to the set of $L$ directions $\theta_l, l = 1, 2, \ldots, L$. We construct a matrix composed of steering vectors corresponding to each potential incident signal direction as its columns: $\mathbf{\Psi} = [\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \ldots, \mathbf{a}(\theta_L)] \in \mathbb{C}^{M \times L}$. In this framework, $\mathbf{\Psi}$ is known and does not depend on the actual incident signal direction $\theta$. Now, in multiple snapshots scenario, the signal matrix is represented by $\mathbf{U}$, where the $l$th row component $\mathbf{U}(l, :) \in \mathbf{U}$ is nonzero only if $\theta_l = \theta_k$ for some $\theta_l$, and in that case, it means $\mathbf{U}(l, :) = \mathbf{s}_k(t)$. Then, (1) can be rewritten as

$$\mathbf{X} = \mathbf{\Psi} \mathbf{U} + \mathbf{N} \quad (20)$$

where the matrices $\mathbf{X}$ and $\mathbf{N}$ are the $M \times N$ array output matrix and the $M \times N$ noise matrix, respectively. Then, DOA estimation can be regarded as a joint-sparse recovery problem, just like MMV.

Under the CS framework, $\mathbf{U}$ can be recovered by exploiting nonadaptive linear projection measurement with a $P \times M$ observation matrix $\mathbf{\Phi}$, when the matrix $\mathbf{\Phi}$ and the matrix $\mathbf{\Psi}$ are incoherent. The MMV problem is that of identifying the row support of the unknown matrix $\mathbf{U}$ from the matrix $\mathbf{Y} \in \mathbb{C}^{P \times N}$ which is given by

$$\mathbf{Y} = [\mathbf{y}(1), \mathbf{y}(2), \ldots, \mathbf{y}(N)] = \mathbf{\Phi} \mathbf{\Psi} \mathbf{U} + \mathbf{\Phi} \mathbf{N}. \quad (21)$$

The single measurement vector (SMV) $\mathbf{y}(t), t = 1, \ldots, N$ constructs the measurement matrix $\mathbf{Y}$.

Because the number of observations $P$ is much smaller than the sparsity signal length $L$, the problem of finding a sparse solution is substantially underdetermined. Under the condition that the signal is $K$-sparse, the conventional approach for solving the underdetermined problem is transformed into solving a convex optimization problem of the following form with $l_{2,1}$ norm minimum:

$$\min \| \mathbf{U} \|_{2,1} \quad \text{s.t.} \quad \mathbf{Y} = \mathbf{\Phi} \mathbf{\Psi} \mathbf{U} + \mathbf{\Phi} \mathbf{N} \quad (22)$$

where $\| \mathbf{U} \|_{g,h}$ is defined as

$$\| \mathbf{U} \|_{g,h} = \left[ \sum_{l=1}^{P} \left( \sum_{n=1}^{N} |\mathbf{U}(l, n)|^g \right)^{h/g} \right]^{1/h}. \quad (23)$$

Here, $g = 2$, and $h = 1$. At present, some algorithms have already been applied to solve the MMV problem in (22), which are based on CS.
B. Proposed DOA Estimation Algorithm Based on OMP

In this section, a CS approach for DOA estimation in the presence of unknown mutual coupling is proposed. Similarly as \( \mathbf{X} \), in (20), \( \hat{\mathbf{X}} \) is expressed as

\[
\hat{\mathbf{X}} = \mathbf{C} \hat{\mathbf{\Psi}} \hat{\mathbf{U}} + \mathbf{N}
\]

(23)

where the definition of \( \hat{\mathbf{U}} \) is similar to \( \mathbf{U} \) whose \( l \)th row corresponds to the possible incident signal coming from \( \theta_l \). Because of the existence of MCM \( \mathbf{C} \), a sparse representation approach cannot be used. Thus, we have to optimize \( \hat{\mathbf{U}} \) and \( \hat{\mathbf{C}} \) simultaneously, and the optimization approach is similar to (22)

\[
\min_{\hat{\mathbf{U}}, \hat{\mathbf{C}}} \| \hat{\mathbf{U}} \|_{2,1}
\]

s.t \( \mathbf{Y} = \hat{\mathbf{\Phi}} \hat{\mathbf{C}} \hat{\mathbf{\Psi}} \hat{\mathbf{U}} + \hat{\mathbf{\Phi}} \mathbf{N} \)  

(24)

where \( \| \hat{\mathbf{U}} \|_{2,1} \) is similarly defined as \( \| \mathbf{U} \|_{2,1} \). However, (24) is a complex nonconvex optimization problem, which we cannot solve in polynomial time. Some measures have been taken to transform (24) into a convex optimization problem. A mutual coupling elimination mechanism proposed in [30] can be utilized to solve the problem (24). The following theorem is needed.

**Theorem 1—[30]:** Define a selection matrix \( \mathbf{F} = [\mathbf{0}_{(M-2p) \times p}, \mathbf{I}_{M-2p} \mathbf{0}_{(M-2p) \times p}] \). \( \mathbf{C} \) and \( \hat{\mathbf{\Psi}} \) have already been defined; then, we have:

\[
\mathbf{F} \hat{\mathbf{\Psi}} = \mathbf{F} \hat{\mathbf{\Psi}} \mathbf{G}
\]

\[
\mathbf{F}^\ast \hat{\mathbf{\Psi}} = \mathbf{F} \hat{\mathbf{\Psi}} \mathbf{G}^\ast
\]

(25)

(26)

where \( \mathbf{G} = [f(v_1), f(v_2), \ldots, f(v_L)] \) and \( f(v_l) = \sum_{p'=-p}^{p'} c_{p'} |v^p| \).

**Proof:** It follows that

\[
\mathbf{F} \hat{\mathbf{\Psi}} = \left[ \begin{array}{cccc}
    v_1^p & v_1^{p+1} & \cdots & v_1^{p+1} \\
    v_2^p & v_2^{p+1} & \cdots & v_2^{p+1} \\
    \vdots & \vdots & \ddots & \vdots \\
    v_{M-p-1}^p & v_{M-p-1}^{p+1} & \cdots & v_{M-p-1}^{p+1} \\
\end{array} \right] 
\]

\[
\times \left[ \begin{array}{ccc}
    f(v_1) \\
    f(v_2) \\
    \vdots \\
    f(v_L) \\
\end{array} \right] 
\]

\[
= \mathbf{F} \hat{\mathbf{\Psi}} \mathbf{G}.
\]

(27)

We can prove (26) similarly as (28); then, the theorem is proved.

Then, novel array output \( \hat{\mathbf{X}} \) constructed by \( \mathbf{F} \) is repressed as

\[
\hat{\mathbf{X}} = \mathbf{F} \mathbf{X} = \mathbf{F} \mathbf{C} \hat{\mathbf{\Psi}} \hat{\mathbf{U}} + \mathbf{F} \mathbf{N}
\]

\[
= \mathbf{F} \hat{\mathbf{\Psi}} \mathbf{G} \hat{\mathbf{U}} + \mathbf{F} \mathbf{N} = \hat{\mathbf{\Psi}} \mathbf{G} \hat{\mathbf{U}} + \mathbf{N}
\]

(28)

where \( \hat{\mathbf{\Psi}} = \mathbf{F} \hat{\mathbf{\Psi}} \) and \( \hat{\mathbf{N}} = \mathbf{F} \mathbf{N} \). From (28), it can be seen that \( \mathbf{F} \mathbf{X} = \hat{\mathbf{\Psi}} (2p+1 : M-2p,:) \). Obviously, only the center submatrix of the array output \( \hat{\mathbf{X}} \) is utilized to reconstruct \( \hat{\mathbf{U}} \). At first glance, it is difficult to understand the idea of abandoning some information that the array receives when estimating DOA. However, the effect of mutual coupling is eliminated by dropping some of the information that the array receives, so that (24) can be transformed into a much simpler convex optimization problem. These points will be elaborated as follows.

The novel covariance matrix \( \hat{\mathbf{R}} \) is similar to \( \mathbf{R} \)

\[
\hat{\mathbf{R}} = \mathbf{E} \{ \mathbf{XX}^\ast \} = \hat{\mathbf{\Psi}} \mathbf{G} \hat{\mathbf{U}} \mathbf{G}^\ast \hat{\mathbf{\Psi}}^\ast + \sigma^2 \mathbf{I}_{M-2p}
\]

(29)

where \( \mathbf{R}_U = \mathbf{E} \{ \mathbf{UU}^\ast \} \) is the covariance matrix of \( \mathbf{U} \) and \( \mathbf{I}_{M-2p} \) is the \( (M-2p) \times (M-2p) \) identical matrix, respectively. It is easy to know that \( \mathbf{G} \mathbf{R}_U \mathbf{G}^\ast \) is diagonal because \( \mathbf{G} \) and \( \mathbf{R}_U \) are diagonal matrices, respectively. Then, (29) can be written in another form as

\[
\hat{\mathbf{R}} = \mathbf{E} \{ \mathbf{XX}^\ast \} = \hat{\mathbf{\Psi}} \mathbf{R}_U \hat{\mathbf{\Psi}}^\ast + \sigma^2 \mathbf{I}_{M-2p}
\]

(30)

where \( \mathbf{R}_U = \mathbf{G} \mathbf{R}_U \mathbf{G}^\ast \) is the novel signal covariance matrix. A very interesting result is shown in (30) that all of the mutual coupling coefficients are included into the novel signal covariance matrix. Thus, there is no need to optimize two variables \( \hat{\mathbf{U}} \) and \( \hat{\mathbf{C}} \) simultaneously.

In order to compensate the aperture loss of discarding the information that the array receives, the vectorization (vec) operator is applied to (30); then, we have

\[
\mathbf{r} = \mathbf{vec} \{ \hat{\mathbf{R}} \} = [\mathbf{\Psi}^\ast \odot \mathbf{\Psi}] \mathbf{S} + \sigma^2 \mathbf{vec} \{ \mathbf{I}_{M-2p} \}
\]

(31)

where \( \mathbf{vec} \{ \cdot \} \) is the vectorization operator that turns a matrix into a vector by stacking the columns of the matrix one below another. \( \mathbf{r} \) is an \( (M-2p)^2 \)-dimensional vector constructed by \( \mathbf{R} \). \( \mathbf{S} \) is an \( (M-2p)^2 \)-dimensional vector whose entries consist of \( \mathbf{R}_U \) with its diagonal entries. \( \odot \) is denoted as the Khatri–Rao (KR) product.

Due to the vectorization operator, the dimension of the novel array manifold matrix \( \mathbf{\Psi}^\ast \odot \mathbf{\Psi} \) is \( (M-2p)^2 \), which improves the degrees of freedom of the array and extends the array aperture. Obviously, the array can be applied to underdetermined DOA estimation after this processing. However, the proposed algorithm does not have this advantage mainly because the problem that we are trying to solve is an SMV problem. However, the proposed algorithm has low computational complexity because the computational complexity of the SMV problem is much lower than that of the MMV problem as described in \( l_1 < SV D \) [13] and JLZA [14].

Then, the observation \( \bar{\mathbf{y}} \) can be acquired based on CS theory by multiplying a \( P \times (M-2p)^2 \) random measurement matrix \( \Phi \). The expression is as follows:

\[
\bar{\mathbf{y}} = \Phi [\hat{\mathbf{\Psi}}^\ast \odot \hat{\mathbf{\Psi}}] \mathbf{S} + \sigma^2 \Phi \mathbf{I}_{(M-2p)^2}
\]

(32)

Thus, (17) can be written as

\[
\min_{\mathbf{S}} \| \mathbf{S} \|_1
\]

s.t \( \| \bar{\mathbf{y}} - \Phi [\hat{\mathbf{\Psi}}^\ast \odot \hat{\mathbf{\Psi}}] \mathbf{S} \|_2^2 \leq \varepsilon \)  

(33)

where \( \varepsilon \) is a regulation parameter which is determined by the power of the observation noise. Then, the problem of
minimizing the $l_1$-norm in the proposed method is solved by the orthogonal matching pursuit (OMP) algorithm [36].

Then, the on-grid DOA estimation algorithm is summarized as follows.

**Algorithm 1 On-Grid DOA estimation based on OMP.**

1: Eliminate the effect of mutual coupling by multiplying the selection matrix $F$, the output of center array is expressed as $x(t)$ based on (8);
2: Construct the novel covariance matrix $\bar{R}$ based on (29);
3: Take the vectorization (vec) operator on $\bar{R}$ to obtain the vector $r$ based on (31);
4: Multiply the random measurement matrix $\Phi$ to obtain the observed vector $y$ in based on (32);
5: Perform the OMP algorithm for minimizing $l_1$-norm in (33), the DOAs of uncorrelated signals can be estimated finally.

VI. OFF-GRID DOA ESTIMATION CONSIDERING TEMPORALLY CORRELATED SOURCE VECTORS

In this section, the characteristic of the temporal correlation between the neighboring snapshot numbers is analyzed based on the data received by the real direction finding system. Then, the DOA estimation considering the temporally correlated source vectors in the presence of unknown mutual coupling is proposed.

A. Temporal Correlation Analysis

In this section, the temporal correlation between the neighboring snapshot numbers is analyzed based on the data received by the real direction finding system. The clock frequency of ADSP TS201 is 435 MHz. The uniform circular array (UCA) is 0.124 m, and the frequency of the incident signals is 6 GHz. Two narrowband far-field signals impinge on the UCA from the direction (175°, 85.5°) and (46°, 78.5°), respectively. The former and latter stand for the azimuth and elevation, respectively. The signal-to-noise ratio (SNR) is fixed at 20 dB. For two stationary signals $s_i(t)$ and $s_k(t)$, the correlation coefficient is defined as

$$\rho_{ik} = \frac{E[s_i(t)s_k^*(t)]}{\sqrt{E[s_i(t)^2]E[s_k(t)^2]}}.$$  

(34)

Then, the correlation coefficient between neighboring snapshot numbers is depicted in Fig. 5. It can be seen that the correlation coefficient between neighboring snapshot numbers is very high. The correlation coefficient is larger than 0.88 at all of the snapshot numbers. This phenomenon is mainly caused by the high sampling rate of the ADSP TS201. Thus, the temporal correlation between the neighboring snapshot numbers is a problem which needs to be solved.

**B. Proposed DOA Estimation Algorithm Based on SBL**

However, the on-grid DOA estimation still has two drawbacks which limit the application of these algorithms. The first one is that the true DOAs of the incident signals may not be on the discrete grids. The second one is that dense discrete grids lead to a highly coherent matrix. It would violate the condition for the sparse signal recovery [37]. Then, an off-grid DOA estimation algorithm is replaced by the on-grid DOA estimation algorithm which is shown in (24).

Similarly as $\bar{R}_{MC}$ given in (17), the estimated covariance matrix of the center array can be written as $\bar{R}_{MC}$ with

$$\bar{R}_{MC} = \bar{R} + \Delta \bar{R}$$  

(35)

where $\Delta \bar{R} = \bar{R}_{MC} - \bar{R}$ is the estimated error. $\Delta \bar{R}$ has been proved to satisfy an asymptotic Gaussian distribution, i.e., vec($\Delta \bar{R}$) $\sim$ AsN(0, $\Sigma_{\Delta \bar{R}}$), where $\Sigma_{\Delta \bar{R}} \triangleq (\bar{R}^H \otimes \bar{R})/N$. Denote $\bar{G} = \bar{R}^{1/2}$, and the $\sqrt{N\bar{G}\Delta \bar{R}\bar{G}^H}$ satisfies the asymptotic standard normal distribution [38]. Then, the novel model used for off-grid DOA estimation can be written as [39]

$$\hat{\bar{R}} = \sqrt{N}\bar{G}((\bar{R}_{MC} - \sigma^2_n I) \bar{G}^H$$  

$$= \sqrt{N}\bar{G}(\bar{\Psi}\bar{R}_{\bar{U}}\bar{\Psi}^H + \Delta \bar{R})\bar{G}^H = \bar{G}\bar{\Sigma}\bar{S} + \bar{N}$$  

(36)

where $\bar{S} = \sqrt{N}\bar{R}_{\bar{U}}\bar{\Psi}^H\bar{G}^H$ and $\bar{N} = \sqrt{N}\bar{G}\Delta \bar{R}\bar{G}^H$. The covariance matrix of $\bar{S}$ satisfies that

$$\Sigma_{\bar{S}} = (\bar{\Sigma}\bar{S}^H)/M$$  

$$= \left(N\bar{R}_{\bar{U}}\bar{\Psi}^H\bar{R}^{-1}\bar{\Psi}\bar{R}_{\bar{U}}^H\right)/M.$$  

(37)

For the high SNR, the effect of noise can be neglected, and we have $\Sigma_{\bar{S}} \approx N\bar{R}_{\bar{U}}/M$. It can be seen that $\Sigma_{\bar{S}}$ is a diagonal matrix, and the row of $\bar{S}$ is orthogonal. Thus, the $\bar{S}(i,:), l = 1, 2, \ldots, L$ satisfies a Gaussian process: $p(\bar{S}(i,:)|\gamma_l, \bar{H}_l) \sim CN(0, \gamma_l\bar{H}_l)$, where $\gamma_l$ is a nonnegative hyperparameter and $\bar{H}_l$ is a positive definite matrix that captures the correlation structure of $\bar{S}(i,:)$.
For the off-grid DOA estimation model [37], the grid interval is defined as \( r = |\theta_2 - \theta_1| \). Assume that \( \theta_l \notin \{\theta_1, \theta_2, \ldots, \theta_L\} \) for some \( k \in 1, 2, \ldots, K \) and that \( \theta_{l_k}, l_k \in \{1, 2, \ldots, L\} \) is the nearest grid point to \( \theta_l \). Based on the linearization, the steering vector \( a(\theta_l) \) can be approximated as

\[
\zeta(\theta_l) \approx \zeta(\theta_{l_k}) + \xi(\theta_{l_k})(\theta_l - \theta_{l_k})
\]

(38)

where \( \xi(\theta_{l_k}) = \zeta'(\theta_{l_k}) \) is the derivative of \( \zeta(\theta_{l_k}) \) with respect to \( \theta_{l_k} \). Denote \( \Phi = [\zeta(\theta_1), \zeta(\theta_2), \ldots, \zeta(\theta_L)] \), \( \tilde{\Phi} = [\xi(\theta_1), \xi(\theta_2), \ldots, \xi(\theta_L)] \), \( \beta = [\beta_1, \beta_2, \ldots, \beta_L]^T \), and \( S = [S^T(1), S^T(2), \ldots, S^T(L)]^T \), and we have

\[
\Theta(\beta) = G\left[\Psi + \tilde{\Phi} \text{diag}(\beta)\right]
\]

(39)

where

\[
\begin{cases}
\beta_l = \theta_l - \theta_{l_k}, & \text{if } k = l_k, \\
\beta_l = 0, & \text{if } k \in \{1, 2, \ldots, K\}, \text{for any } k \neq l_k,
\end{cases}
\]

(40)

\( l = 1, 2, \ldots, L \), with \( l_k = 1, 2, \ldots, L \) and \( \theta_{l_k} \), the nearest grid to a source \( \theta_l, k \in \{1, 2, \ldots, K\} \). Thus, the off-grid model for sparse representation is given by

\[
\hat{\mathbf{R}} = \Theta(\beta) \mathbf{S} + \mathbf{N}
\]

(41)

where \( \Theta(\beta) \in \mathbb{C}^{M \times L}, \mathbf{S} \in \mathbb{C}^{L \times M} \), and \( \mathbf{N} \in \mathbb{C}^{M \times M} \). Thus, the equivalent number of snapshots is \( M \).

In order to estimate the DOAs of the incident signals, the support of the matrix \( \mathbf{S} \) and the off-grid difference \( \beta \) are both to be estimated.

Based on (41), the entries of \( \mathbf{N} \) are independent and satisfy the asymptotic normal distribution, i.e., \( p(\mathbf{N}) = \Pi_{m=1}^M \text{AsN}(\mathbf{N}(m,:)|0, \mathbf{I}) \). According to the definition of sparse block Bayesian learning given in [40], (41) can be written as

\[
\mathbf{y} = \mathbf{D} s + \mathbf{n}
\]

(42)

where \( \mathbf{y} = \text{vec}(\mathbf{R}^T) \), \( \mathbf{D} = \Theta(\beta) \otimes \mathbf{I}_M \), \( \mathbf{s} = \text{vec}(\mathbf{S}^T) \), and \( \mathbf{n} = \text{vec}(\mathbf{N}^T) \). Based on the statistical assumption of \( \mathbf{S} \), the prior for \( \mathbf{s} \) is given by \( p(s|\gamma, \mathbf{H}) \sim \text{CN}(0, \Sigma_0) \), where \( \mathbf{H} = \text{diag}(\gamma) \), \( \gamma = [\gamma_1, \gamma_2, \ldots, \gamma_L] \) with \( \Sigma_0 = \mathbf{G} \otimes \mathbf{H} \). Based on the assumption given in [39], the sparse prior of \( \gamma \) is assumed by \( p(\gamma|\rho) = \prod_{l=1}^L \Gamma(\gamma_l|1, \rho) \), where \( \rho \) is an empirical parameter and usually fixed to a small value like 0.01. Similarly as the distribution of \( \beta \) given in [37], the uniform prior distribution is used as well, i.e., \( \beta \sim \text{U}([-r/2, r/2]) \).

According to [39, eq. (6)], the posterior density of \( \mathbf{s} \) can be expressed as \( p(s|\gamma, \mathbf{H}, \beta) \sim \text{CN}(\mu_S, \Sigma_S) \), with \( \mu_S = \Sigma_0 \mathbf{D}^H(I + \Sigma_0 \mathbf{D} \mathbf{D}^H)^{-1}\mathbf{y} \) and \( \Sigma_S = (\Sigma_0^{-1} + \mathbf{D} \mathbf{D}^H)^{-1} \). The parameter update rule is given as follows.

For \( \beta \), we can obtain the equation as follows based on the derivation of [37]:

\[
\beta_{\text{new}} = \arg \min_{\beta \in [-5, 5]^N} \{\beta^T \mathbf{W} \beta - 2\mathbf{v}^T \beta\}
\]

(43)
Then, the support of $S$ and the parameter $\beta$ can be estimated. The off-grid DOA estimation is finally achieved via

$$\theta_k = \tilde{\theta}_k + \beta_l. \quad (52)$$

Then, the off-grid DOA estimation algorithm is summarized as follows.

**Algorithm 2** Off-Grid DOA estimation based on SBL.

1: Eliminate the effect of mutual coupling by multiplying the selection matrix $F$, the output of center array is expressed as $\tilde{x}(t)$ in (8);
2: Construct the novel covariance matrix $\tilde{R}_{MC}$, then calculate $G$;
3: Calculate $\tilde{R}$ based on (36);
4: initialize $\gamma$, $H$, $\beta$;
5: while $||\gamma^{i+1} - \gamma^i||_F / ||\gamma^i|| > \tau$ do
6: Construct the $\Theta^i(\beta)$ and $T^i$, respectively;
7: Calculate $\tilde{S}^i$ and $\Sigma^i_{\tilde{S}}$ based on (46) and (47), respectively;
8: Update $\gamma^i$, $H^i$, $\beta^i$ based on (48), (49), (50) and (51), respectively;
9: end while;
10: The DOAs of uncorrelated signals can be estimated finally via (52).

**VII. DISCUSSIONS**

Compared with the traditional DOA estimation algorithms such as the MUSIC-based algorithms, the computational complexity of the on-grid and off-grid DOA estimation algorithms proposed in this paper is much larger than that of the MUSIC-based algorithms. However, the DOA estimation accuracy of the proposed algorithms is much higher than that of MUSIC algorithms especially in small snapshot numbers. Fortunately, the mobile cloud computing (MCC) technique [42], [43] can be applied to reduce the runtime of the proposed algorithms. As a rapid development area, mobile cloud computation (MCC) has become a promising technology. MCC is a special part of cloud computing, which is suitable for the computing on mobile devices. The massive computing, storage, and software services can be executed flexibly using much lower energy consumption in a scalable and virtualized manner. Based on MCC, many applications with large computational complexity can be executed in the mobile devices.

It is noteworthy that the solution (19) and (33) may be different due to the “blind angle” phenomenon introduced in [30], i.e.,

$$C_{\tilde{a}}(\tilde{\theta}_l) = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_{M-1} \\ C_M \end{bmatrix} = C \begin{bmatrix} 1 \\ \tilde{a} \\ \vdots \\ \tilde{a}^{M-1} \end{bmatrix} = D_{\tilde{a}}(\tilde{\theta}_l) = c(\tilde{\theta}_l)_{\tilde{a}}(\tilde{\theta}_l). \quad (53)$$

Equation (60) explains the phenomenon. $\tilde{a}$ is short for $a(\tilde{\theta}_l)$, $c(\tilde{\theta}_l)$ is defined as

$$c(\tilde{\theta}_l) = \left(2 \sum_{p'=1}^{p} c_{p'} \cos \left(2p' \pi \sin(\theta_l)d/\lambda \right) + 1 \right) \quad (54)$$

$$C_1 = c_{p} \tilde{a}^{-p} + \cdots + c_1 \tilde{a}^{-1} + 1 + c_1 \tilde{a} + \cdots + c_p \tilde{a}^p \quad (55)$$

$$C_2 = c_{p} \tilde{a}^{-p} + \cdots + c_1 \tilde{a}^{-1} + 1 + c_1 \tilde{a} + \cdots + c_p \tilde{a}^p \quad (56)$$

$$C_{M-1} = c_{p} \tilde{a}^{-p} + \cdots + c_1 \tilde{a}^{-1} + 1 + c_1 \tilde{a} + \cdots + c_p \tilde{a}^p \quad (57)$$

$$C_M = c_{p} \tilde{a}^{-p} + \cdots + c_1 \tilde{a}^{-1} + 1 + c_1 \tilde{a} + \cdots + c_p \tilde{a}^p. \quad (58)$$

Whenever there is one incident signal with its DOA $\theta_j = \theta_l, l = 1, 2, \ldots, L$, we have

$$c(\tilde{\theta}_l)a(\theta_l) = 0. \quad (59)$$

Equation (60) implies that the $j$th incident signal is not contained. Therefore, at some particular angles, the array is blind and cannot receive any incident signal from these directions. Thus, these angles are called “blind angles.” This phenomenon would happen when the estimated number of signals is less than the actual number of signals. Fortunately, for given mutual coefficients, $c(\tilde{\theta}_l)$ is a continuous function, and the probability of $c(\tilde{\theta}_l) = 0$ is approximately zero, which means that the “blind angles” phenomenon rarely happens in practice. More details can be found in [30].

**VIII. SIMULATION RESULTS**

In order to illustrate the performance of the proposed algorithm, the numerical simulation results are presented in this section. We compare the performance of the proposed algorithms with MUSIC and JLZA [14]. The compressive sampling length of the proposed algorithm is $P = 50$. The computational complexity of the proposed algorithm is much larger than that of the subspace algorithms. Thus, a multiresolution grid refinement strategy is used for off-grid DOA estimation [13]. At first, a rough grid is applied to estimate DOA; then, a refine grid is applied around the spectrum peak, and the DOA estimator is updated until the grid is fine enough. Here, the resolution of the rough grid is selected as $1^\circ$; and the refined grid set is set as $0.1^\circ$. For the off-grid DOA estimation, the grid interval is set to be $2^\circ$. 

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We consider a scenario in which a ULA with $M = 16$ elements is separated by half a wavelength of the narrowband far-field incident signals. The number of mutual coupling coefficients is $p = 2$, $c_1 = 0.4500 + i0.5362$, and $c_2 = 0.2598 - i0.1500$. As shown in Fig. 6, two uncorrelated sources impinge on the array from the directions $-10.1^\circ$ and $19.1^\circ$. The SNR = 10 dB, and the number of snapshots is 100. The grid resolution is $0.1^\circ$ with $L = 1801$. Here, 200 independent simulations are carried out. We compare the normalized spatial spectrum of the proposed on-grid algorithm with those of the MUSIC with unknown mutual coupling (MUSIC-UMC) and JLZA. It can be seen that the spatial spectrum of MUSIC-UMC is more flat than that of the other two algorithms. For JLZA, there is a little bias around the spectrum peak. The proposed algorithm gives the sharpest spectrum peak of the aforementioned algorithms. Another scenario with four uncorrelated sources coming from $-20.4^\circ$, $0.6^\circ$, $20.8^\circ$, and $45.7^\circ$ is shown in Fig. 7. It indicates that the proposed on-grid algorithm has a good estimation performance when the unknown mutual coupling exists.

Figs. 8 and 9 show the root-mean-square error (rmse) and the detection probability with different SNRs, respectively. The number of the snapshots is 200, and the other simulation conditions are identical with Fig. 4. As shown in Fig. 8, the rmse of MUSIC-UMC is larger that of the other two algorithms. This performance reduction of MUSIC algorithm is mainly caused by the information loss of mutual coupling. The rmse of MUSIC-UMC and JLZA are close when the SNR is high. Although the rmse of the proposed on-grid DOA estimation algorithm is smaller than MUSIC-UMC and JLZA algorithms. However, the grid mismatch affects the performance of the on-grid DOA estimation algorithm. The off-grid DOA estimation achieves the smallest rmse of all algorithms. A similar plot depicting the detection probability of different algorithms is shown in Fig. 9. The proposed on-grid and off-grid DOA estimation algorithms outperform the other methods. The detection probability of the on-grid DOA estimation algorithm is larger than that of JLZA at low SNR. The MUSIC-UMC requires about $-2$ dB to reach the 100% detection probability. The
In this paper, two novel DOA estimation algorithms are proposed in the presence of unknown mutual coupling in order to solve some existing problems in ITS of MCM of ULA. For the on-grid DOA estimation algorithm, in order to compensate the aperture loss of discarding information that the array receives, the array aperture is extended by the vectorization operator. For the off-grid DOA estimation algorithm, the SBL algorithm is applied, which avoids the grid mismatch of the on-grid DOA estimation algorithm. The computer simulation verifies the effectiveness of the proposed algorithms. With the help of MCC, the proposed algorithm can estimate the DOAs of targets in real time. It can be known that the angle information contained in the target echo can be used in various conditions. We will explore more applications in the vehicle industrial using DOA estimation algorithms and reduce the computational complexity of the proposed algorithm in the future work.

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