Fast Logistics Vehicle Localizing Based on EMVS-MIMO Radar and Edge Computing

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ABSTRACT This article focuses on logistics vehicle active localizing using multiple-input multiple output (MIMO) radar, and a fast localizing architecture that integrates edge computing and cloud platform is proposed. The core of the proposed methodology is to measure the angles of logistics vehicle using bistatic MIMO radars, which are configured with coprime electromagnetic vector sensors (EMVS). Unlike the existing localization systems, the proposed localizing architecture provides two-dimensional (2D) angle estimation, i.e., 2D direction-of-departure (DOD) estimation and 2D direction-of-arrival (DOA) estimation, and it offers additional polarization status of the logistics vehicle. A parallel factor (PARAFAC) estimator is developed. Firstly, it estimate the factor matrices via PARAFAC decomposition. Thereafter, the elevation angle estimation is accomplished via least squares (LS) technique, which are ambiguous due to the coprime property of the EMVS. The azimuth angle estimation are followed via vector cross-product. Besides, the polarization information of the targets can be obtained via LS approach. The above process is accomplished at cloud platform. Finally, the localization of the logistics vehicle is achieved with the estimated 2D angles, which is computational friendly and achieved via edge computing. Detailed analyses concerning degree-of-freedom, identifiability, complexity as well as Cramér-Rao bound (CRB) are provided. To show the effectiveness of the proposed architecture, numerical simulations have been designed.

INDEX TERMS Logistics vehicle localizing, multiple-input multiple output radar, electromagnetic vector sensor, coprime array, parallel factor.

I. INTRODUCTION

Internet of vehicles (IoV) is an interesting topic for further logistics vehicle [1]. According to the concept of IoV, it is able to provide comfortable deriving services, e.g., driverless, collision warning, online interaction. Most of the smart services are based on low-delay (in the microsecond range) and accurate vehicle location awareness. Owing to the high latency, traditional global positioning systems (GPS) are unable to fulfill the localizing requirement. As an alternative to the GPS, the cooperative positioning becomes very popular recently. Typical options include radar, lidar, camera, ultrasonic, wireless access points. Usually, the above techniques are based four principles, namely time-of-arrival, time-difference-of-arrival, radio-signal-strength, and angle-of-arrival (AOA) [2], [3]. The AOA approaches become a nice choice since they can be easily and accurately measured via sensor array. Herein, the existing AOA approaches can be divided into two categories, the passive method and the active schemes. The former utilizes the wireless communication system to measure the AOA of the base stations, while the latter adopts the array radar to calculate the relative AOA of the vehicle with respect to the transmit sensors and the receive sensors, i.e., direction-of-departure (DOD) and direction-of-arrival (DOA). Comparatively speaking, the active schemes are more appearing from the perspective of complexity and reliability, at the cost of additional hardware cost. In this article, we focus on the active logistics vehicle localizing using multiple-input multiple output (MIMO) radar. The main task is to measure the DOD and DOA of logistics vehicle via MIMO radar.

The estimation of DOD and DOA in bistatic MIMO radar is well known as a highly nonlinear issue. Up to now, extensive super-resolution algorithms have been reported, e.g., Capon, estimation method of signal parameters via rotational invariance technique (ESPRIT) [4], [5], multiple signal classification (MUSIC) algorithm [6]–[8], propagator...
method (PM) [9], maximum-likelihood (ML) estimator [10], tensor approach [11], [12]. Generally, the spatial spectrum search strategies (e.g., Capon, MUSIC, ML) are computationally unfriendly, and they may encounter the off-grid issue. ESPRIT is famous for its efficiency, since it can obtain closed-form solution for DOA estimation. Tensor approach, however, often provides better estimation accuracy than the above matrix-based ones, since it can make full use of the multidimensional structure of the array measurement. There are two kinds of tensor, i.e., Tucker tensor and parallel factor (PARAFAC) tensor. The former is similar to singular value decomposition (SVD), which decompose a tensor into product of a core tensor and unitary matrices. The latter is a special case of the former, i.e., the core tensor is a diagonal tensor, and the factor matrices consist of rank-one tensors. Usually, the Tucker decomposition can be directly obtained via higher-order decomposition (HOSVD), while the PARAFAC decomposition can be achieved via iterative least square (LS) technique, which can provides better estimation performance than the former.

It should be point out that, as reported in the literature, most of the existing works focus on one-dimensional (1D) AOA estimation using 1D scaler sensors, e.g., uniform linear array (ULA), nonuniform linear array. A small part has pay attention to two-dimensional (2D) DOA estimation using nonlinear scaler sensor geometry, e.g., circular array, L-shape array, rectangular array, cube array, arbitrary sensor manifold. Recently, electromagnetic vector sensor (EMVS) has being a hotspot, since an EMVS is able to provide 2D DOA estimation [13]. Unlike the traditional scaler sensor, the estimation problem with EMVS array is much more complex, as it involves four-dimensional angle estimation, i.e., 2D direction angle (elevation angle and azimuth angle) estimation and 2D polarization parameter (auxiliary polarization angle and polarization phase difference). EMVS has bring new insight into target localization to MIMO radar, since it is able to offer 2D-DOD estimation and 2D-DOA estimation using 1D array geometries. Furthermore, additional polarization status of the target are capable, which is helpful in detecting stealth target.

With respect to 2D-AOA estimation using EMVS-MIMO radar, several efforts have been devoted. Inspired by the ESPRIT, the method that combine ESPRIT with vector cross-product was firstly investigated in [14], in which the elevation angles (transmit elevation angle and receive elevation angle) are obtained via the rotational invariant property of the array, then the azimuth angles are estimated via vector cross-product. Similarly, the approaches that integrate traditional methods (e.g., PM, HOSVD) and vector cross-product were introduced in [15], [16]. Unfortunately, the algorithm in [14]–[16] show limited performances, since the virtual aperture of the EMVS-MIMO radar is hurt. Besides, additional pairing calculation is required, making these algorithms more complex. In [17], an improved PM estimator is derived. Unlike the PM-like approach in [15], the improved PM estimator achieves the elevation angles via the rotation invariance property of the whole virtual array, i.e., it makes full use of the array virtual aperture and thus provides improved AOA estimation. Moreover, neither does it require eigendecomposition of the array covariance matrix, nor does it need pairing the estimated angles. As a results, it outperform the algorithms in [14] and [15]. Taking the multidimensional nature of the array measurement into account, an PARAFAC-like estimator was introduced in [18]. By performing PARAFAC decomposition on the array measurement, it can achieve the factor matrices that contain the AOA of the targets. Thereafter, it achieves the elevation angles via ESPRIT of the array measurement. Similarly, the vector cross-product were adopted to obtain the azimuth angles. Like the PM-like estimator in [17], the PARAFAC-like estimator can achieve automatically paired 2D-DOD and 2D-DOA estimation. Moreover, it performs better than [14]–[17].

A common characteristic that the schemes in [14]–[18] share is that the ULA geometries are utilized. To avoid phase ambiguity, the inter-element distance between sensors should be smaller than half-wavelength. Consequently, the virtual aperture of the transmit/receive array is limit. Besides, splitting adjacent sensor distance would cause the mutual coupling problem [19], leading to decreased estimation performance. As a promising array manifold, the coprime array has aroused extensive attention [20]–[22]. A coprime array can be divided into two sparse ULA, the inter-element distances of which are coprime numbers. The AOA that separately estimated from the two subarrays are ambiguous, but they can be uniquely determined via coprime characteristic. Owing to increased array aperture, coprime array offers much accurate estimation performance than ULA. The coprime EMVS array has been turned out to be effective in improving the parameter estimation performance [23]. However, few works have been done concerning parameter estimation in EMVS-MIMO radar.

The contributions of this article can be summarized into the following items:

**Contribution 1.** A novel logistics vehicle localizing architecture is proposed. As shown in Fig. 1, the proposed system
is consist of three parts, the measurement part, the cloud platform and the edge computing part. The bistatic MIMO radar is configured to measure the AOA of the logistics vehicle. The transmitters and the receivers are connect to the cloud and edge computing section, which provides calculation service for the localizing system. Unlike the active localizing architectures in [2], [3], the AOA estimation is accomplished at cloud, while the localizing calculation transformed to the measure ends, which are equipped with edge computing module.

Contribution 2. We proposed the a new EMVS-MIMO configuration, in which the transmit sensors and the receive sensors are coprime EMVS. Different with the existing ULA-configuration, in which the transmit sensors and the receive sensors are designed to measure the AOA of the logistics vehicle.

Contribution 3. A fast PARAFAC estimator is derived in this article. Unlike the PARAFAC algorithm in [18], the proposed estimator offers more accurate AOA estimation performance. It is verified both theoretically and practically. It is analyzed in terms of degree-of-freedom, identifiability, complexity as well as Cramér-Rao bound (CRB). Moreover, numerical simulations are designed to show its superiority.

Some notations are used throughout this article. Bold capital letters and bold lowercase letters, e.g., e.g., A and a, denote matrices and vectors, respectively. The $M \times M$ identity matrix is denoted by $I_M$, and the $M \times N$ full zeros matrix is denoted by $0_{M \times N}$; The superscript $(X^T, X^H, X^{-1}$ and $(X)^T$ stand for the operations of transpose, Hermitian transpose, inverse and pseudo-inverse, respectively; $\otimes$ and $\odot$ represent, respectively, the Kronecker product and the Khatri-Rao product; $\| \cdot \|_F$ accounts for the Frobenius norm; diag $\{ \cdot \}$ denotes the diagonalization operation; angle $(a)$ is to get the phase angle of $a$, in radian; $E \{ \cdot \}$ is to get the mathematical expectation; The vector-cross-product between $e_1 = [e_1, e_2, e_3]^T$ and $e_2 = [e_4, e_5, e_6]^T$ is defined as

$$
\begin{align*}
e_1 \otimes e_2 &= \begin{bmatrix} 0 & -e_3 & e_2 \\
e_3 & 0 & -e_1 \\
e_2 & e_1 & 0 \end{bmatrix} \begin{bmatrix} e_4 \\
e_5 \\
e_6 \end{bmatrix}.
\end{align*}
$$

II. TENSOR PRELIMINARIES AND PROBLEM FORMULATION

A. TENSOR PRELIMINARIES

A tensor is a multidimensional array [24]. Some useful definitions concerning tensor and tensor operation are listed as follows:

Definition 1 (Fibers): Let $\mathcal{X} \in \mathbb{C}^{i_1 \times i_2 \times \ldots \times i_N}$ denotes an $N$-th order tensor. The fibers are the higher-order analogue of matrix rows and columns. A mode-$n$ fiber of $\mathcal{X}$ is an $I_n$-dimensional column vector obtained from $\mathcal{X}$ by varying the index $i_n$ and keeping the other indices fixed.

Definition 2 (Tensor Unfolding): The mode-$n$ unfolding of an $N$-th order tensor $\mathcal{X} \in \mathbb{C}^{i_1 \times i_2 \times \ldots \times i_N}$ is denoted by $[\mathcal{X}]_{(n)}$. The $(1, i_2, \ldots, i_N)$-element of $\mathcal{X}$ maps to the $(i_n, j)$-th element of $[\mathcal{X}]_{(n)}$, where $j = 1 + \sum_{k=1, k \neq n}^{N} (i_k - 1)j_k$ with $J_k = \prod_{m=1, m \neq n}^{k-1} i_m$.

Definition 3 (Mode-$n$ Tensor-Matrix Product): The mode-$n$ product of an $N$-order tensor $\mathcal{X} \in \mathbb{C}^{i_1 \times i_2 \times \ldots \times i_N}$ and a matrix $A \in \mathbb{C}^{I_n \times I_k}$, is denoted by $\mathcal{Y} = \mathcal{X}_A^{(n)} A$.

Definition 4 (PARAFAC Decomposition): The PARAFAC decomposition factorize a tensor into a sum of component rank-one tensors. The PARAFAC decomposition of an rank-$R$ tensor $\mathcal{X} \in \mathbb{C}^{i_1 \times i_2 \times \ldots \times i_N}$ can be expressed as

$$
\mathcal{X}_{i_1, i_2, \ldots, i_N} = A_{i_1,k} A_{i_2,k} \ldots A_{i_N,k} \tag{1}
$$

where the lowerscript denotes the index of the entity. In mode-$n$ matrix unfolding format, (1) can be formulated as

$$
[\mathcal{X}]_{(n)} = A_n [A_{n+1} \odot \ldots \odot A_N \odot A_1 \odot \ldots \odot A_{n-1}]^T \tag{2}
$$

where $G = \text{diag} \{ [g_1, g_2, \ldots, g_K] \} \in \mathbb{C}^{K \times K}$ is a diagonal matrix.

B. SIX COMPONENT EMVS

Let’s introduce a six-component EMVS array scenario, as shown in Fig. 2. Each EMVS has six ends, three of them measure the electronic field and three of them sense the magnetic wave impinging on an $N$-element EMVS array, the noiseless received array measurements can be formulated as [13]

$$
y(t) = \sum_{k=1}^{K} [a_k \otimes b_k] s_k(t) \tag{3}
$$

where $t$ is the snapshot index, $a_k \in \mathbb{C}^{N \times 1}$ is the $k$-th receive steering vector. $s_k(t)$ denotes the $k$-th source signal. $b_k \in \mathbb{C}^{6 \times 1}$ is the spatial response vectors of the EMVS, which satisfies

$$
b_k = C_k v_k \tag{4}
$$

FIGURE 2. Illustration of six component EMVS array.
Suppose there are \( K \) far-field logistics vehicles, the 2D-DOD and 2D-DOA of the \( k \)-th logistics vehicle are denoted by \( (\theta_{t,k}, \phi_{t,k}) \) and \( (\theta_{r,k}, \phi_{r,k}) \), respectively, where \( \theta_{t,k}, \theta_{r,k} \) are the elevation angles, and \( \phi_{t,k}, \phi_{r,k} \) are the azimuth angles. The matched outputs can be formulated as
\[
y(\tau) = [A_r \odot B_t \odot A_r \odot B_r] s(\tau) + n(\tau) \tag{8}\]
where \( \tau \) is the snapshot index. \( s(\tau) = [s_1(\tau), s_2(\tau), \ldots, s_K(\tau)]^T \) stands for the reflect coefficient vector of the logistics vehicle. \( n(\tau) \) is the Gaussian noise vector with zero mean and variance \( \sigma^2 \). \( A_r = [a_{r,1}, a_{r,2}, \ldots, a_{r,K}] \in \mathbb{C}^{M \times K}, \ B_t = [b_{t,1}, b_{t,2}, \ldots, b_{t,K}] \in \mathbb{C}^{N \times K} \), \( A_r = [a_{r,1}, a_{r,2}, \ldots, a_{r,K}] \in \mathbb{C}^{N \times K} \) and \( B_r = [b_{r,1}, b_{r,2}, \ldots, b_{r,K}] \in \mathbb{C}^{N \times K} \) denote the response matrices, respectively. The \( k \)-th steering vectors of \( A_r, B_t, A_r, B_r \) are
\[
a_{r,k} = \left[ e^{jN_k(\tau_1-1)\pi \sin \theta_{t,k}}, \ldots, e^{jN_k N \pi \sin \theta_{t,k}}, 1, \\
e^{-jM_k \pi \sin \theta_{r,k}}, \ldots, e^{-jM_k (N_k-1) \pi \sin \theta_{r,k}} \right]^T \tag{9a}
\]
\[
a_{t,k} = \left[ e^{jM_k \pi \sin \theta_{r,k}}, \ldots, e^{jM_k (N_k-1) \pi \sin \theta_{r,k}} \right]^T \tag{9b}
\]
\[
b_{t,k} = [b_{t,k,1}, b_{t,k,2}, \ldots, b_{t,k,L}]^T \tag{9c}
\]
\[
b_{r,k} = [b_{r,k,1}, b_{r,k,2}, \ldots, b_{r,k,L}]^T \tag{9d}
\]
In practice, we can collect \( L \) snapshots and form a measurement matrix \( Y = [y_1, y_2, \ldots, y_L] \in \mathbb{C}^{36MN \times L} \). As a result, (8) can be rewritten as
\[
Y = \sum_{k=1}^{K} [a_{t,k} \odot b_{t,k} \odot a_{r,k} \odot b_{r,k}] f_{i,k} + N
= [A_t \odot B_t \otimes A_r \odot B_r] F + N
= [D_t \odot D_r] F + N \tag{10}
\]
where \( N = [n_1, n_2, \ldots, n_L] \in \mathbb{C}^{36MN \times L} \) is the noise measurement with variance \( \sigma^2 \). \( B_t = [b_{t,1}, b_{t,2}, \ldots, b_{t,K}] \in \mathbb{C}^{N \times K}, A_r = [a_{r,1}, a_{r,2}, \ldots, a_{r,K}] \in \mathbb{C}^{M \times K}, F = [f_1, f_2, \ldots, f_L] \in \mathbb{C}^{L \times K} \) with \( f_i = [f_{i,1}, f_{i,2}, \ldots, f_{i,K}]^T \). \( D_t = A_t \odot B_t \) and \( D_r = A_r \odot B_r \) are the virtual direction matrices. Our object is to obtain the 2D-DOD and 2D-DOA estimation from \( Y \).

C. PROBLEM FORMULATION

Now we consider a coprime EMVS-MIMO radar, which is consist of \( M \)-element transmit EMVS and \( N \)-element receive EMVS. More specifically, we assume that both the transmit EMVS and the receive EMVS are distributed in coprime geometries, as depicted in Fig. 3. Each coprime array consists of two subarrays, denoted as Subarray 1 and Subarray 2. Both of them are ULA and share the same reference sensor. We assume there are \( M_t \) transmit EMVS in Subarray 1, and \( N_t \) transmit EMVS in Subarray 2, where \( M_t \) and \( N_t \) are coprime integers, \( M = M_t + N_t - 1 \). The adjacent distances of Subarray 1 and Subarray 2 are \( N_t \lambda / 2 \) and \( M_t \lambda / 2 \), respectively, where \( \lambda \) is the carrier wavelength. Similarly, there are \( M_r \) receive EMVS in Subarray 1, and \( N_r \) receive EMVS in Subarray 2, \( M_r \) and \( N_r \) are coprime integers with \( N = M_r + N_r - 1 \), and the subarrays are distributed as that of the transmit antennas.

![Illustration of Coprime EMVS array.](image)

Subarray 1
Subarray 2

\( M \) 2
\( N \)

\( \bullet \) : Shared EMVS

**FIGURE 3.** Illustration of Coprime EMVS array.

with
\[
C_k = \begin{bmatrix}
\cos \phi_k \cos \theta_k & -\sin \phi_k \\
\sin \phi_k \cos \theta_k & \cos \phi_k \\
-\sin \theta_k & 0 \\
-\sin \phi_k \cos \theta_k & -\cos \phi_k \\
\cos \phi_k & -\sin \phi_k \cos \theta_k \\
0 & \sin \theta_k
\end{bmatrix} \tag{5}
\]
and
\[
v_k = \begin{bmatrix}
\sin \gamma_k e^{j\eta_k} \\
\cos \gamma_k
\end{bmatrix} \tag{6}
\]
where \( \theta_k \) denotes the \( k \)-th elevation angle, \( \phi_k \) is the azimuth angle, \( \gamma_k \) is the \( k \)-th auxiliary polarization angle, and \( \eta_k \) is the \( k \)-th polarization phase difference.

Define \( b_k = \begin{bmatrix} e_k \end{bmatrix} \), where \( e_k \in \mathbb{C}^{3 \times 1} \) accounts for the electric-field vector, \( h_k \in \mathbb{C}^{3 \times 1} \) denotes the magnetic-field vector. According to [13], the vector-cross-product between \( e_k \) and \( h_k \) fulfills
\[
p_k = e_k \odot h_k
= \begin{bmatrix}
\sin \gamma_k \cos \phi_k \\
\sin \gamma_k \sin \phi_k \\
\sin \theta_k \sin \phi_k \\
\cos \theta_k
\end{bmatrix} \tag{7}
\]
Notably, the 2D-AOA is uniquely determined by \( p_k \).

III. THE PROPOSED ESTIMATOR

A. PARAFAC MODEL

Actually, \( Y \) exhibits abundant tensor nature and it can be formulated into a third-order tensor as [18]
\[
Z = \mathcal{I}_{3 \times K} \otimes D_t \otimes D_r \otimes F + N \tag{11}
\]
where \( N \in \mathbb{C}^{3M \times 6N \times L} \) is the rearranged noise tensor. To estimate the factor matrices \( D_t, D_r \) and \( F \), we need to minimize
\[
\min_{D_t, D_r, F} \| Z - \mathcal{I}_{3 \times K} \otimes D_t \otimes D_r \otimes F \|_F \tag{12}
\]
The above issue can be solved by the trilinear alternative least squares (TALS) technique. Obviously, three matrices...
can be got via unfolding $Z$ as $Z_1 = [Z]_{(1)}^T$, $Z_2 = [Z]_{(2)}^T$, respectively. According to Definition 4, we have

$$Z_1 = (D_r \odot F) D_r^T$$  \hspace{1cm} (13a)

$$Z_2 = (F \odot D_r) D_r^T$$  \hspace{1cm} (13b)

$$Z_3 = (D_r \odot D_r) F^T$$  \hspace{1cm} (13c)

As a result, (12) can be solved via

$$\min_{D_r, D_r, F} \left\| Z_1 - (D_r \odot F) D_r^T \right\|_F$$  \hspace{1cm} (14a)

$$\min_{D_r, D_r, F} \left\| Z_2 - (F \odot D_r) D_r^T \right\|_F$$  \hspace{1cm} (14b)

$$\min_{D_r, D_r, F} \left\| Z_3 - (D_r \odot D_r) F^T \right\|_F$$  \hspace{1cm} (14c)

Notably, there are three factor matrices $D_r, D_r, F$. Having fixed all but one of them, the above issues will reduce to least squares (LS) problems. For example, if $D_r$ and $F$ are known, to estimate $D_r$, we can compute

$$\hat{D}_r^T = (D_r \odot F)^\dagger Z_1$$  \hspace{1cm} (15)

Likewise, if $F$ and $D_r$ are obtained, $D_r$ can be get via calculating

$$\hat{D}_r^T = (F \odot D_r)^\dagger Z_2$$  \hspace{1cm} (16)

Similarly, once $D_r$ and $D_r$ are known, $F$ can be achieved via computing

$$\hat{F}^T = (D_r \odot D_r)^\dagger Z_3$$  \hspace{1cm} (17)

In TALS, the iteration of (15)-(17) will repeat before algorithm convergence. To accelerate the iteration, the COMFAC algorithm is utilized [18], which only need several iteration steps.

**B. AMBIGUOUS ELEVATION ANGLE ESTIMATION**

It has been pointed out in Kruskal’s theorem [24], if the Kruskal ranks of the factor matrices $D_r, D_r$ and $F$, denoted by $k_{D_r}, k_{D_r}$ and $k_F$, respectively, fulfill

$$k_{D_r} + k_{D_r} + k_F \geq 2K + 3$$  \hspace{1cm} (18)

then the estimated factor matrices (denoted by $\hat{D}_r$, $\hat{D}_r$ and $\hat{F}$, respectively) are unique up to permutation and scaling of columns, i.e.,

$$\hat{D}_r = D_r \Pi \Delta_1 + N_1$$  \hspace{1cm} (19a)

$$\hat{D}_r = D_r \Pi \Delta_2 + N_2$$  \hspace{1cm} (19b)

$$\hat{F} = F \Pi \Delta_3 + N_3$$  \hspace{1cm} (19c)

where $N_1, N_2$ and $N_3$ are the fitting errors. $\Pi \in \mathbb{C}^{K \times K}$ is the permutation matrix. $\Delta_1, \Delta_2$ and $\Delta_3$ are $K \times K$ scaler matrices, which are diagonal matrices and satisfy $\Delta_1 \Delta_2 \Delta_3 = I_K$.

Define $J_r = \begin{bmatrix} 0_{(M_r-1)\times 1} & 0_{(M_r-1)\times N_r} \end{bmatrix} \in \mathbb{C}^{(M_r-1)\times M_r}$,

$$J_r = \begin{bmatrix} 0_{(M_r-1)\times 1} & 0_{(M_r-1)\times N_r} \end{bmatrix} \in \mathbb{C}^{(M_r-1)\times M_r},$$

$$J_r = \begin{bmatrix} 0_{(N_r-1)\times (M_r-1)} & 0_{(N_r-1)\times 1} \end{bmatrix} \in \mathbb{C}^{(N_r-1)\times (M_r-1)},$$

$$J_r = \begin{bmatrix} 0_{(N_r-1)\times (M_r-1)} & I_{N_r-1} \end{bmatrix} \in \mathbb{C}^{(N_r-1)\times (M_r-1)}.$$ Let

$$J_r = \begin{bmatrix} 0_{(M_r-1)\times 1} & 0_{(M_r-1)\times N_r} \end{bmatrix} \in \mathbb{C}^{(M_r-1)\times N_r}.$$ 

Let

$$J_r = \begin{bmatrix} 0_{(M_r-1)\times 1} & 0_{(M_r-1)\times N_r} \end{bmatrix} \in \mathbb{C}^{(M_r-1)\times N_r},$$

$$J_r = \begin{bmatrix} 0_{(N_r-1)\times (M_r-1)} & 0_{(N_r-1)\times 1} \end{bmatrix} \in \mathbb{C}^{(N_r-1)\times (M_r-1)},$$

$$J_r = \begin{bmatrix} 0_{(N_r-1)\times (M_r-1)} & I_{N_r-1} \end{bmatrix} \in \mathbb{C}^{(N_r-1)\times (M_r-1)}.$$ 

Then we have

$$\hat{\theta}_{1,k} = \arcsin \{ -\angle (\lambda_{1,k}) \}$$  \hspace{1cm} (24)

Since $\Pi$ is a permutation matrix (its entities are ones or zeros), it can be estimated via

$$\hat{\Pi} = \text{round} \{ \Re \{ Q \} \}$$  \hspace{1cm} (25)

Similarly, we can get

$$\hat{\theta}_{2,k} = \arcsin \{ -\angle (\lambda_{2,k}) \}$$  \hspace{1cm} (27a)

$$\hat{\theta}_{1,k} = \arcsin \{ -\angle (\lambda_{1,k}) \}$$  \hspace{1cm} (27b)
\[ \hat{\theta}_{1,2,k} = \arcsin \{-\angle(\hat{\lambda}_{2,2,k})\} \]  

Since \( N_1 \pi \sin \theta_{1,k} \) and \( M_2 \pi \sin \theta_{2,k} \) are within \([-N_1 \pi, N_1 \pi]\) and \([-M_2 \pi, M_2 \pi]\), respectively, but the mapping angle (\( \cdot \)) is wrapped within the range \([-\pi, \pi]\), the transmit elevation angles that estimated from (27) are ambiguous. So does the receive elevation angles.

**C. UNIQUE ELEVATION ANGLE DETERMINATION**

It is worth noting that \( \hat{\theta}_{1,1,k} \) are obtained from Subarray 1, while \( \hat{\theta}_{2,k} \) are estimated from Subarray 2. Although they are ambiguous, they are different due to the coprime characteristic between \( M_1 \) and \( N_1 \). Taking the unique transmit elevation angle determination as an example, we will show how to recover the unique elevation angles.

Owing to the fact the the inter-element spacing of Subarray 1 is \( N_1 \lambda/2 \), there should be \( N_1 \) solutions including the one obtained from (24). According to (22), the relation between the \( n_t \) \((n_t = 1, 2, \ldots, N_1)\) solution \( \hat{\theta}_{1,1,k}(n_t) \) and the estimation \( \hat{\theta}_{1,1,k} \) can be expressed as

\[ \sin \hat{\theta}_{1,1,k} = \sin \hat{\theta}_{1,1,k} - 2(n_t - 1)/N_1 \]  

(28)

For Subarray 2, there should be \( M_2 \) solutions \( \hat{\theta}_{1,1,k}(m_t) \) \((m_t = 1, 2, \ldots, M_2)\) including the one achieved via (27a), a similar conclusion can be get as

\[ \sin \hat{\theta}_{2,2,k} = \sin \hat{\theta}_{2,2,k} - 2(m_t - 1)/M_2 \]  

(29)

Due to the coprime-ness between \( M_1 \) and \( N_1 \), the \( k \)-th correct estimation can be obtained by averaging the nearest solutions of \( \hat{\theta}_{1,1,k} \) and \( \hat{\theta}_{2,2,k} \), i.e.,

\[ \hat{\theta}_{t,k} = \frac{\hat{\theta}_{1,1,k} + \hat{\theta}_{2,2,k}}{2} \]  

(30)

where \( \hat{\theta}_{1,1,k} \) and \( \hat{\theta}_{2,2,k} \) account for the associate angles of the two closest solutions. Similarly, we can get the unique receive elevation angle estimates \( \hat{\eta}_{t,k} \).

**D. AZIMUTH ANGLE AND POLARIZATION PARAMETERS ESTIMATION**

Since the first element of both \( \mathbf{A}_r \) and \( \mathbf{A}_r \) are ones, \( \mathbf{B}_t \) and \( \mathbf{B}_r \) can be estimated via

\[ \hat{ \mathbf{B}_t } = \hat{ \mathbf{D}_t } (1:6,:) \]  

(31a)

\[ \hat{ \mathbf{B}_r } = \hat{ \mathbf{D}_r } (1:6,:) \]  

(31b)

where \( \hat{ \mathbf{D}_t } (1:6,:) \) denotes the first six rows of \( \hat{ \mathbf{D}_t } \). Let \( \mathbf{e}_{t,k} \in \mathbb{C}^{3 \times 1} \) and \( \mathbf{h}_{r,k} \in \mathbb{C}^{3 \times 1} \) account for the first and the last three elements of the \( k \)-th column of \( \hat{ \mathbf{B}_t } \), respectively. Then we calculate

\[ \hat{\mathbf{p}}_{t,k} = \frac{\mathbf{e}_{t,k}}{\| \mathbf{e}_{t,k} \| F} \oplus \frac{\mathbf{h}_{r,k}}{\| \mathbf{h}_{r,k} \| F} \]  

(32)

As a result, \( \hat{\phi}_{t,k} \) can be estimated via

\[ \hat{\phi}_{t,k} = \arctan \left( \frac{\hat{\mathbf{p}}_{t,k}(2)}{\hat{\mathbf{p}}_{t,k}(1)} \right) \]  

(33)

Finally, the transmit polarization parameters can be estimated via

\[ \hat{\eta}_{t,k} = \arctan \left( \frac{\mathbf{g}_{t,k}(2)}{\mathbf{g}_{t,k}(1)} \right) \]  

(35a)

\[ \hat{\eta}_{t,k} = \arctan \left( \frac{\mathbf{g}_{t,k}(2)}{\mathbf{g}_{t,k}(1)} \right) \]  

(35b)

Notably, \( \{\hat{\theta}_{t,k}, \hat{\phi}_{t,k}, \hat{\eta}_{t,k}\} \) are paired automatically. In a similar way, we can recover the receive polarization parameter parameters.

**E. LOGISTICS VEHICLE POSITIONING USING AOA**

After the 2D-AOA (DOD or DOA) of the logistics vehicle has been obtained, its position can be achieved according to the mathematical relationship between the AOA and position. As depicted in Fig. 4, suppose that the transmit EMVS position is \((X_{0,1}, Y_{0,1}, Z_{0,1})\) and the receive EMVS position is \((X_{0,2}, Y_{0,2}, Z_{0,2})\), the \( k \)-th logistics vehicle is located at \((P_{x,k}, P_{y,k}, P_{z,k})\). We have the following relationships

\[ \tan \theta_{t,k} = \frac{P_{y,k} - Y_{0,1}}{P_{z,k} - Z_{0,1}} \]  

(36a)

\[ \tan \phi_{t,k} = \frac{P_{y,k} - Y_{0,1}}{P_{x,k} - X_{0,1}} \]  

(36b)

\[ \tan \theta_{r,k} = \frac{P_{y,k} - Y_{0,2}}{P_{z,k} - Z_{0,2}} \]  

(36c)

\[ \tan \phi_{r,k} = \frac{P_{y,k} - Y_{0,2}}{P_{x,k} - X_{0,2}} \]  

(36d)

The coordinates of \((P_{x,k}, P_{y,k}, P_{z,k})\) can be unique determined by utilizing the above relations.
TABLE 1. Comparison of the identifiability.

| Method     | Identifiability       |
|------------|-----------------------|
| ESPRIT     | \(\min\{6(M-1), 6(N-1)\}\) |
| PM         | \(\min\{36N(M-1), 36M(N-1)\}\) |
| HOSVD      | \(\min\{6(M-1), 6(N-1)\}\) |
| PARAFAC    | \((6M+6N+L-3)/2\)      |
| Proposed   | \((6M+6N+L-3)/2\)      |

IV. ALGORITHM ANALYSIS

A. DEGREE-OF-FREEDOM

According to the flowchart of the proposed estimator, the accuracy of elevation angle estimation is highly related to the virtual aperture of EMVS-MIMO radar. Obviously, the transmit aperture of the proposed method is \(M_t N_t \lambda/2\), and the receive aperture of the EMVS array is \(M_r N_r \lambda/2\). Therefore, the virtual aperture of the proposed EMVS-MIMO is \(M_t N_t M_r N_r \lambda/2\). In contrast, the transmit aperture of the methods in [14] (marked with ‘ESPRIT’), [16] (marked with ‘HOSVD’), [17] (marked with ‘PM’), and [18] (marked with ‘PARAFAC’) is \(M \lambda/2\), and the receive aperture of methods in ESPRIT, HOSVD, PM and PARAFAC is \(N \lambda/2\). Usually, we have \(M_t N_t > M\) and \(M_r N_r > N\), thus the proposed method offers larger aperture than that in [14]-[17].

B. IDENTIFIABILITY

The identifiability of the proposed estimator is equal to the maximum \(K\). According to (18), the proposed estimator is unique if \(k_d + k_r + k_F \geq 2K + 3\). Usually, the Kruskal rank of a matrix is equal to the maximum rank of a matrix. As a result, \(\max\{k_d\} = 6M\), \(\max\{k_r\} = 6N\) and \(\max\{k_F\} = L\). Then (18) becomes

\[
6M + 6N + L \geq 2K + 3
\]

which reveals the maximum identifiability of the proposed estimator is \((6M + 6N + L - 3)/2\). For comparison purpose, we list the identifiability of the algorithms in ESPRIT, PM, HOSVD and PARAFAC, which are shown in Table 1. Since \(L\) is usually much greater than \(MN\), the proposed estimator has the same identifiability to PARAFAC, which is better than ESPRIT, PM and HOSVD.

C. COMPLEXITY

In this subsection, we compare the main complexity (which is equal to the number of complex multiplication) of the proposed estimator to the existing algorithms. The main complexity of the proposed estimator is TALS, which is on the order \(O\{6MK^2 + 6NK^2 + LK^2\}\). It has a slight more complexity than PARAFAC, since it requires to determine the unique elevation angle estimation. For comparison purpose, we list the main complexities of ESPRIT, PM, HOSVD and PARAFAC in Table 2. It is shown both PARAFAC and the proposed estimator are more efficient than ESPRIT and HOSVD, but they are maybe less efficient than PM.

D. CRB

Let the \(8K \times 1\) unknown angle vector as \(\Theta = \left[\theta_1, \ldots, \theta_K, \varphi_1, \ldots, \varphi_K\right]^T\). According to [18], the CRB on \(\Theta\) is given by

\[
\text{CRB} = \frac{\sigma^2}{2L} \left[ \text{Re} \left\{ \left( \mathbf{D}^H \mathbf{\Sigma}^{-1} \mathbf{D} \right) \otimes \left( R_\gamma^f \otimes I_{8\times8} \right) \right\} \right]^{-1}
\]

where \(\mathbf{D} = \left[ \frac{\partial \mathbf{r}_1}{\partial \theta_1}, \ldots, \frac{\partial \mathbf{r}_K}{\partial \theta_K}, \frac{\partial \mathbf{r}_1}{\partial \phi_1}, \ldots, \frac{\partial \mathbf{r}_K}{\partial \phi_K} \right]\), \(\mathbf{\Sigma}^{-1} = J_{36MN} - \mathbf{D} (\mathbf{D}^H \mathbf{D})^{-1} \mathbf{D}^H\), \(\mathbf{D} = \mathbf{D}_t \otimes \mathbf{D}_r\), \(\mathbf{d}_k\) is the \(k\)-th column of \(\mathbf{D}\), \(R_\gamma^f = \frac{1}{\tau} F^H F\).

V. SIMULATION RESULTS

To verify the localization performance of the proposed estimator, 200 Monte-Carlo trials are performed. We consider a scenario that a bistatic EMVS-MIMO radar system is equipped with \(M\) transmitters and \(N\) receivers, both of them are EMVSs with coprime geometries, as illustrated in Figure 3. We assume that the number of sensor in the transmit subarrays are \(M_t\) and \(M_r\), \(M_t + M_r - 1 = M\), respectively, and the number of sensor in the receive subarrays are \(N_t\) and \(N_r\), \(N_t + N_r - 1 = N\), respectively. Suppose that \(K = 3\) far-field logistics vehicles appearing in the same range bin of the radar system, and their direction parameters are \(\theta = (40^\circ, 20^\circ, 30^\circ), \varphi = (15^\circ, 25^\circ, 35^\circ), \gamma = (10^\circ, 22^\circ, 35^\circ), \eta = (36^\circ, 48^\circ, 56^\circ), \theta' = (24^\circ, 38^\circ, 16^\circ), \phi' = (21^\circ, 32^\circ, 55^\circ), \gamma' = (42^\circ, 33^\circ, 60^\circ), \eta' = (17^\circ, 27^\circ, 39^\circ)\), respectively. \(L = 200\) snapshots are collected. The average root mean square error (RMSE) on elevation angle estimation and the average running time (ART) are utilized to evaluate estimation performance. For comparison purpose, the performances of ESPRIT, PM, HOSVD and PARAFAC with ULA setup are added. In addition, the CRB corresponding to coprime geometry is added.

In the first example, we illustrate the scatter results of the proposed estimator, where \(M_t = 4, N_t = 5 (M = 8), M_r = 5\) and \(N_r = 6 (N = 10)\), where signal-to-noise ratio (SNR) is set to 15dB. The results of 2D-DOD estimation and 2D-DOA estimation are given in Fig.5 and Fig.6, respectively. Notably, the 2D-DOD and 2D-DOA can be accurately estimated and correctly paired. It is evident that the proposed estimator is able to estimate the 2D-DOA of the logistics vehicle.

In the second example, we test the average RMSE performance versus SNR, where \(M_t = 4, N_t = 5 (M = 8), M_r = 5\) and \(N_r = 6 (N = 10)\). As displayed in Fig.7, all the algorithms perform worse at low SNR regions. With the increasing SNR, all the algorithms will provide improving
RMSE. Moreover, the proposed estimator outperform all the compared algorithms. The above improvement benefits from two aspects. On the one hand, the PARAFAC model enables the proposed estimator to offer much better performance than the existing algorithms. On the other hand, the coprime geometries in the proposed architecture occupy larger degree-of-freedom than the existing ULA manifold. On the other hand, the coprime geometry provides larger aperture than the ULA. In this example, the transmit aperture is $M_t N_t \lambda / 2 = 10\lambda$, the receive aperture is $M_r N_r \lambda / 2 = 15\lambda$, while the apertures associate to the compared algorithms are $4\lambda$ and $5\lambda$, respectively. Obviously, the proposed framework occupies larger aperture than the compared methods.

Finally, we test the RMSE and the ART performance versus $N$, where SNR is fixed at 0dB and $M_r$ is set to 5, other conditions are the same to that in the first example (to simplify the simulation, $N_r$ is vary from 3 to 21 with interval 3 and ignore those can divide 5, so that $M_r$ and $N_r$ are coprime numbers). Fig. 8 illustrates the RMSE result, while Fig. 9 presents the ART result. It indicates that the proposed estimator provides better RMSE performance than all the compared algorithms when $N > 7$. However, it has larger complexity than PARAFAC, but it is much more efficient than ESPRIT and HOSVD. In addition, it may has lower complexity than PM when $N$ is large enough.
VI. CONCLUSION

In this article, a logistics vehicle localizing that EMVS-MIMO radar, edge computing and cloud platform is proposed. The core is to measure the AOA of logistics vehicle using MIMO radars, after edge computing one can obtain the detailed position of the logistics vehicle. Unlike the existing EMVS-MIMO geometry, the coprime are adopted here, which offers more accurate AOA estimation than ULA frameworks. Herein, a PARAFAC estimator is developed, which is computationally friendly. Detailed analyses have been provided and numerical simulations have been designed. The proposed estimator should be very effective in further massive MIMO configuration.

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