Joint OAM Radar-Communication Systems: Target Recognition and Beam Optimization

Wen-Xuan Long, Graduate Student Member, IEEE, Rui Chen, Member, IEEE, Marco Moretti, Member, IEEE, Wei Zhang, Fellow, IEEE, and Jiandong Li, Fellow, IEEE

Abstract—Orbital angular momentum (OAM) radars are able to estimate the azimuth angle and the rotation velocity of multiple targets without relative motion or beam scanning. Moreover, OAM wireless communications can achieve high spectral efficiency (SE) by utilizing a set of information-bearing modes on the same frequency channel. Benefitting from the above advantages, in this paper, we design a novel radar-centric joint OAM radar-communication (radCom) scheme based on uniform circular arrays (UCAs), which modulates information signals on the existing OAM radar waveform. In details, we first propose an OAM-based three-dimensional (3-D) super-resolution position estimation and rotation velocity detection method, which can accurately estimate the 3-D position and rotation velocity of multiple targets without beam scanning. Then, we derive the posterior Cramér-Rao bound (PCRB) of the OAM-based estimates and, finally, we analyze SE of the integrated system. To achieve the best trade-off between imaging and communication, the transmitted integrated OAM beams are optimized by means of an exhaustive search method. Both mathematical analysis and simulation results show that the proposed radar-centric joint OAM RadCom scheme can accurately estimate the 3-D position and rotation velocity of multiple targets while ensuring the SE of the communication receiver, which can be regarded as an effective supplement to existing joint RadCom schemes.

Index Terms—Orbital angular momentum (OAM), joint radar-communication (RadCom), target recognition, posterior Cramér-Rao bound (PCRB), beam optimization, uniform circular array (UCA).

I. INTRODUCTION

 Novel service requirements are the driving force behind the evolution of wireless communication networks. The rapid development of emerging applications, such as holographic video, digital twin, virtual reality and auto-pilot driving, results in a neverending growth in mobile data traffic. It is reported that the capacity of next generation wireless communication networks will reach 100 times that of the existing 5G networks [1], [2]. To meet these requirement, more and more high frequency bands such as millimeter-wave and terahertz bands are being licensed [3]. Unfortunately, this further leads to increased congestion of the frequency spectrum where existing radar and other sensing systems reside. To solve this problem, the concept of a novel joint radar-communication (RadCom) system is proposed, in which the previously competing radar sensing and communication operations can be implemented simultaneously by sharing a single hardware platform and a joint signal processing framework. Based on design priorities and the underlying signal, existing joint RadCom schemes can be classified into communication-centric schemes, radar-centric schemes and joint design schemes. Due to the potential close cooperation between radar sensing and wireless communications, joint RadCom schemes are recognized as a key approach to significantly improving spectrum efficiency (SE), reducing device size, cost and power consumption [4].

In recent years, significant progress in the research of radar-centric joint RadCom systems has been made [4], [5], [6]. In [7], the concept of the joint RadCom was proposed for the first time, providing new ideas for the research of radar and communication technologies. In [8], several joint sharing schemes, such as time-sharing, frequency-sharing and beam-sharing, are discussed in details, laying the foundation for the design of RadCom systems in different scenarios. In [9], the continuous phase modulation is first used to embed information into polyphase-coded frequency-modulated radar waveforms, paving the way for the radar-centered integrated waveform designs. In [10], an orthogonal frequency division multiplexing (OFDM)-based integrated waveform is applied to a radar-centered multiple-input multiple-output (MIMO)
RadCom system, achieving two-dimensional (2-D) position estimation and velocity detection of targets while communicating. In [11], a novel inter-carrier interference (ICI)-aware sensing algorithm is applied to a radar-centered MIMO-OFDM RadCom system to estimate delay-Doppler-angle parameters of multiple targets in high-mobility scenarios. In [12], a phase-modulated-based integrated waveform optimization scheme is applied to a radar-centered MIMO RadCom system to find the best trade-off between radar and communication performances.

However, there are still several technical challenges for the practical application of existing radar-centered joint RadCom schemes. A specific problem is that in the radar-centered RadCom scenarios, especially in the typical scenario shown in Fig.1, the existing joint RadCom schemes cannot realize the type classification and dynamic detection of targets without relative motion or beam scanning. The reason behind is that the plane electromagnetic (EM) waves used in the existing radar-centered joint RadCom systems cannot carry the azimuth and rotation velocity information of targets without relative motion or beam scanning. One promising approach to solve this problem is to employ vortex EM waves into the radar-centered joint RadCom systems. The phase front of the vortex EM wave carrying OAM rotates with azimuth exhibiting a helical structure $e^{j\ell\phi'}$ in space [13], where $\phi'$ is the transverse azimuth and $\ell$ is an unbounded integer defined as OAM topological charge or OAM mode number. This helical phase structure provides a new degree of freedom for radar application and information transmission.

For radar sensing, the vortex EM wave carrying OAM can be seen as multiple plane EM waves that simultaneously illuminate the target from continuous azimuth, achieving thus angular diversity without relative motion or beam scanning. Therefore, OAM-based schemes are regarded as a promising approach to provide the azimuthal resolution without beam scanning [15], [16], [17], [18], [19], [20], [21]. In [18] and [19], OAM-carrying waves are employed on the existing synthetic aperture radar (SAR) and inverse synthetic aperture radar (ISAR) for the first time, which realize the high-resolution azimuthal imaging of universal targets, providing a firm basis for the applications of vortex EM waves in radar realms as well as the development of the three-dimensional (3-D) imaging technique. In [21], a novel OAM-based 3-D position estimation method combining back-projection (BP) and spectral estimation is proposed for the first time, breaking the limit of elevation resolution in conventional vortex EM imaging and achieving 3-D forward-looking imaging. Moreover, in particular, when vortex EM waves illuminate spinning targets, the rotational Doppler shift caused by spinning targets is proportional to the spinning velocity and OAM mode [22]. Based on this property, OAM-based radars can also be used to estimate the spinning velocity of targets even when there is no radial motion between the radar and targets [23], [24], [25]. In [24], a novel motion vector decomposition method is proposed in OAM radar to detect the rotational velocity and the tilt angle of targets, laying a good foundation for OAM-based rotating target detection. The work in [25] presents an OAM-based rotating target detection method, which combines linear and rotational Doppler separation and short-time Fourier transform (STFT)-based parameter estimation with the objective of achieving a more accurate estimation of the rotational parameters, such as rotation velocity, rotation radius and tilt angle. To sum up, OAM imaging technology has been deeply studied. However, how to modulate the communication information on the existing OAM radar waveform to apply to the typical radar-centered RadCom scenario shown in Fig.1 is still an open problem.

Furthermore, for wireless communications, OAM-based schemes enable a novel coaxial multiplexing approach, which utilizes a set of information-bearing modes on the same frequency channel to achieve high SE [26], [27], [28], [29], [30], [31], [32], [33], [34], [35]. In [27], a wireless transmission experiment based on OAM is realized for the first time by successfully multiplexing two different radio signals at the same frequency. Moreover, a 4 Gbps uncompressed video transmission link over a 60 GHz OAM radio channel is implemented in [28]. In [30], a $2 \times 2$ antenna aperture architecture, where each aperture multiplexes two OAM modes, is implemented in the 28 GHz band achieving a 16 Gbit/s transmission rate. In [35], a communication link with a transmission rate of over 200 Gbit/s is obtained by multiplexing five dual-polarized OAM modes (mode number $\ell = 0, \pm 1, \pm 2$) in the 28 GHz band.

In the past decade OAM-based radar sensing and communications have been investigated in parallel without much overlapping. In practice, they have quite a few commonalities in terms of signal processing algorithms, devices and, to a certain extent, system architecture. Meanwhile, they can also potentially share the spectrum. Considering the problems faced by the existing radar-centered joint RadCom schemes and inspired by the OAM imaging schemes [15], [16], [17], [18], [19], [20], [21], [23], [24], [25], we propose a first radar-centric joint OAM RadCom scheme that includes 3-D super-resolution position estimation, rotation velocity detection and specific target communication. The novelty and major contributions of this paper are summarized as follows:
1) We present a first radar-centric joint OAM RadCom scheme based on uniform circular arrays (UCAs), which modulates information signals on the existing OAM radar waveform by digital modulation. By taking full advantage of the phase structure of OAM beams, the proposed OAM RadCom scheme can effectively estimate the azimuth angle and rotation velocity of targets without beam scanning, while at the same time communicating with a target.

2) We discuss a novel OAM-based multi-target imaging method, which combines the multiple signal classification (MUSIC) and STFT algorithms to achieve 3-D super-resolution position estimation and rotation velocity detection of multiple targets. According to the unique expression of OAM echo signals, we first design a novel search vector for the MUSIC-based position estimation method, which performs a 2-D search for the amplitude and phase of OAM echo signals in the frequency and OAM mode domains respectively, thus achieving the 3-D super-resolution imaging of multiple targets without beam scanning. Moreover, we discuss a STFT-based rotation velocity detection method, which can estimate the rotation velocity of multiple targets simultaneously by taking full advantage of the rotational Doppler characteristics of OAM echo signals, providing a basis for distinguishing the type of targets.

3) The imaging and communication performances of the proposed OAM RadCom system are analyzed by deriving for the first time the posterior Cramér-Rao bound (PCRB) of the OAM-based target imaging. Thereafter, the transmitted integrated OAM beams are optimized by minimizing the PCRB under the constraints dictated by the requirements of the communication part.

The remainder of this paper is organized as follows. Based on the feasibility of generating and receiving OAM beams by UCAs [31], [36], we model the UCA-based radar-centric joint OAM RadCom system in Section II. In Section III, the OAM-based 3-D position estimation and rotation velocity detection methods are proposed. After that, we analyze the PCRB and SE of the joint OAM RadCom system, and optimize the transmitted integrated OAM beams in Section IV. Simulation results are shown in Section V and conclusions are summarized in Section VI.

Notations: Unless otherwise specified, matrices are denoted by bold uppercase letters (i.e., $A$), vectors are represented by bold lowercase letters (i.e., $a$), and scalars are denoted by normal font (i.e., $a$). $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^{-1}$ and $(\cdot)$ stand for the transpose, Hermitian transpose, inverse and Moore-Penrose pseudo-inverse of the matrices. $\|\cdot\|$ and $\text{Re}[\cdot]$ stand for the modulus and the real part of the complex numbers. $\mathbb{E}\{\cdot\}$ denotes the statistical expectation.

II. JOINT OAM RADAR-COMMUNICATION SYSTEM

A. System Model

Employing UCA is a popular way to generate and receive radio OAM beams due to its simple structure and the multi-mode multiplexing ability [15], [32], [33], [36]. Thus, we consider a UCA-based radar-centric joint OAM RadCom system as shown in Fig.1, which consists of one dual-function transmitter with an $M$-element UCA, one radar receiver with an $N$-element UCA, and $Q$ targets each with a single communication antenna within the main lobe of integrated beams. To simplify the mathematical descriptions that follow, we assume that the dual-function transmit and radar receive UCAs are co-located and have the same radius so that a target in the far-field is at the same spatial angle with respect to both the transmitter and receiver.

In the proposed joint OAM RadCom system, the dual-function transmitter periodically transmits integrated OAM beams modulated with information. For easier analysis, we suppose that the transmitter sends data only to a specific target in each period. Then, the specific target would receive integrated OAM signals. Moreover, the radar receiver would receive OAM echo signals from all targets. Therefore, by transmitting integrated OAM signals, information can be transmitted to the specific target, and the state parameters of all the targets can be estimated by OAM echo signals at the radar receiver. Moreover, we assume that the wireless communication between the dual-function transmitter and the specific target is performed through a line of sight (LoS) transmission and the communication channel can be accurately estimated [32], [33], [34].

B. Signal Model

To provide the range-angle-dependent beam pattern for distinguishing multiple targets, we consider an OAM-OFDM-based signal scheme as shown in Fig.2. In the proposed radar-centric joint OAM RadCom system, we assume that the dual-function transmitter sends integrated signals by $U$ OAM modes ($U \leq M$) and $W$ subcarriers. To avoid inter-mode interference, we suppose that the $U$ integrated OAM signals are transmitted sequentially in a specific sequence during each period [16], [20], [37]. Meanwhile, to embed communication information into integrated OAM beams, we introduce $M_p$-ary PSK in each transmitted OAM waveform. Moreover, considering the different gains of different mode integrated OAM beams, we design a weight factor $A_u$ for the power distribution among different mode OAM beams to optimize the performances of the system. Then, the $w$-th signals transmitted by the $m$-th transmit element at the $w$-th subcarrier can be expressed as

$$x_m(t_u, k_w) = A_u e^{j\phi_w}e^m s(t_u, k_w), \quad m = 1, 2, \ldots, M, \quad (1)$$

where $i$ is the imaginary unit, $\phi_w = 2\pi(m - 1)/M$ is the azimuthal angle of the $m$-th transmit element, $s(t_u, k_w) = e^{j\phi_w}$ is the $u$-th integrated OAM symbol at the $w$-th subcarrier, $\phi_w \in [0, \frac{2\pi}{M_p}, \ldots, \frac{2\pi(m_p-1)}{M_p}]$, $k_w = 2\pi f_w/c$ is the wave number corresponding to subcarrier frequency $f_w$, $c$ is the speed of light in vacuum, $A_u$ is the weight of the $u$-th integrated OAM symbol with $\sum_{u=1}^{U} |A_u|^2 = 1$.

Then, for an arbitrary point $P^w(r_t, \theta_t, \phi_t)$ in the far field at arbitrary time $t$, the electric field intensity $E_{R^w}(r_t, t_u, k_w)$ generated by the dual-function transmitter can be
written as [38] and [34]
\[
E_T(r_t, \ell_t, k_w) = \sum_{m=1}^{M} x_m(\ell_u, k_w) \int |r_t - r_m|^{-\ell} e^{ik_w |r_t - r_m|} dV_m
\]
(2)

where \(r_t\) is the position vector of \(P'(r_t, \theta_t, \phi_t)\), \(j\) is the current density of the dipole, \(\mu_0\) is the magnetic permeability in the vacuum, \(\omega_w = 2\pi f_w\) is the circular frequency, \(d\) is the electric dipole length, \(\int dV_m\) is the integral for the dipole in the \(m\)-th element of the dual-function transmit UCA, \(J_{\ell_u}(\cdot)\) is the \(\ell_u\)-th order Bessel function of the first kind, \(R\) is the radius of UCAs. In (2), (a) applies the approximation \(|r_t - r_m| \approx r_t\) for amplitudes and \(|r_t - r_m| \approx r_t - r_m\) for phases in the far field, where \(r_t\) is the unit vector of \(r_t\), \(R_m = R(x' \cos \phi_v + y' \sin \phi_v)\), \(x'\) and \(y'\) are the unit vectors of X-axis and Y-axis of the coordinate system at the transmit/receive UCA, respectively, and (b) holds when \(M\) is large enough.

1) OAM Radar Echo Signal Model: We assume that the radar receiver continually receives OAM echo signals, even when the dual-function transmitter is transmitting integrated OAM signals. Although partially integrated OAM signals in this case will leak to the radar receiver, the transmission leakage can be restrained by transmission leakage cancellation techniques, such as antenna isolation and adaptive interference cancellation. Therefore, in this paper, the transmission leakage is ignored.

Assuming that the \(q\)-th target is discretized into \(P\) ideal scattering points, the baseband signals received by the \(n\)-th element of the radar receive UCA can be written as
\[
E^p_R(\ell_u, k_w) = \sum_{q=1}^{Q} \sum_{p=1}^{P} E_T(r^q_t, \ell_u, k_w) \sigma_{q_p} \int |r^q_t - r_n|^{-\ell} e^{ik_w |r^q_t - r_n|} dV_n + n(\ell_u, k_w)
\]
(3)

where \(r^q_t\) and \(\sigma_{q_p}\) are the position vector and the radar cross section (RCS) of the \(p\)-th scattering point in the \(q\)-th target, \(r_n = R(x' \cos \phi_v + y' \sin \phi_v)\), \(\phi_v = 2\pi (n - 1)/N\) is the azimuthal angle of the \(n\)-th receive element, \(\int dV_n\) is the integral for the dipole in the \(n\)-th element of the radar receive UCA, \(n(\ell_u, k_w)\) is additive white Gaussian noise (AWGN) with zero mean and variance \(\xi^2\).

After that, all the signals received by the \(N\) elements of the radar receiver are combined, and the OAM echo signal on the \(u\)-th mode at the \(w\)-th subcarrier can be expressed as
\[
E^u_R(\ell_u, k_w) = \sum_{n=1}^{N} E^u_R(\ell_u, k_w) + n(\ell_u, k_w)
\]
(4)

where \((r^q_t, \theta^q_t, \phi^q_t)\) is the coordinate of the \(p\)-th scattering point in the coordinate system of the transmit/receive UCA at the time instant \(t\). Thereafter, how to perform OAM imaging at the radar receiver based on (4) will be detailed in Section III.

2) Specific Target Communication Signal Model: For the specific target whose centroid is located at \((\bar{x}_t, \bar{\theta}_t, \bar{\phi}_t)\), the received equivalent baseband signal on the \(u\)-th OAM mode at the \(w\)-th subcarrier can be expressed as
\[
y_q(\ell_u, k_w) = \sum_{m=1}^{M} h^q_m(k_w) x_m(\ell_u, k_w) + z_q(\ell_u, k_w)
\]
(5)
where
\[ h_{m}^{\tilde{a}}(k_w) \approx \frac{\beta}{2k_w r_{1}^{q_p}} \exp \left[ -i k_w r_{1}^{q_p} - i k_w R \sin \theta_{1}^{q_p} \cos(\varphi_{1}^{q_p} + \varphi_{m}) \right] \]

is the channel coefficient from the \( m \)-th element of the transmit UCA to the receive antenna of the specific target, \( \beta \) models all constants relative to the antenna elements and their patterns [32], and \( z_q(\ell_u, k_w) \) is the AWGN with zero mean and variance \( \sigma^2 \). Thereafter, how to detect the received signals at the specific target to recover communication data will be specified in Section IV.

III. OAM-BASED ROTATING TARGET IMAGING

In this section, we propose a novel OAM-based multi-target imaging method combining MUSIC and STFT algorithms, so that it can detect the rotation velocity of multiple targets while it performs 3-D super-resolution imaging, providing a basis for distinguishing the type of target.

A. OAM-Based 3-D Position Estimation

1) Problem Formulation: After the radar receiver is bit synchronized, the OAM echo signal on the \( u \)-th mode at the \( w \)-th subcarrier in (4) can be simplified as
\[
E_R^{'}(\ell_u, k_w) = -\frac{E_R(\ell_u, k_w)}{|\eta(\ell_u, E_w)|^2} s(\ell_u, k_w)^* \cdot l_u^{q_p} \\
= \sum_{q=1}^{Q} \sum_{p=1}^{P} \sigma_{q_p} e^{i2k_w r_{1}^{q_p}} e^{i k_w R \sin \theta_{1}^{q_p}} J_0(k_w R \sin \theta_{1}^{q_p}) \\
\times \sum_{q=1}^{Q} \sum_{p=1}^{P} \sigma_{q_p} e^{i2k_w r_{1}^{q_p}} e^{i k_w R \sin \theta_{1}^{q_p} + n'(\ell_u, k_w)},
\]

where \( \eta(\ell_u, k_w) = -j A_w \mu_{0} \omega^{2} \sigma_{u_w} s(\ell_u, k_w) \) consists of the known parameters of the radar receiver, \( n'(\ell_u, k_w) \) is the noise. Then, all the signals received on the \( U \) OAM modes at the \( W \) subcarriers can be collected in the matrix
\[
E_R = \begin{bmatrix}
E_R^{'}(\ell_1, k_1) & E_R^{'}(\ell_1, k_2) & \cdots & E_R^{'}(\ell_1, k_W) \\
E_R^{'}(\ell_2, k_1) & E_R^{'}(\ell_2, k_2) & \cdots & E_R^{'}(\ell_2, k_W) \\
\vdots & \vdots & \ddots & \vdots \\
E_R^{'}(\ell_U, k_1) & E_R^{'}(\ell_U, k_2) & \cdots & E_R^{'}(\ell_U, k_W)
\end{bmatrix}.
\]

(7)

For easier analysis, the number of targets is assumed to be known to the radar receiver a priori [39], [40].

The aim of 3-D position estimation is to obtain the distance \( r_{1}^{q_p} \), the azimuthal angle \( \varphi_{1}^{q_p} \) and the elevation angle \( \theta_{1}^{q_p} \) of each scattering point of the targets from the elements of the matrix (7). From (6), we observe that the azimuthal angle \( \varphi_{1}^{q_p} \) is coupled with the OAM mode number \( \ell_u \) and so is \( r_{1}^{q_p} \) with \( k_w \). The elevation angle \( \theta_{1}^{q_p} \) is associated with both \( \ell_u \) and \( k_w \). Therefore, we propose to estimate \( \{\theta_{1}^{q_p}, \varphi_{1}^{q_p}\}|p = 1,2,\ldots,P, q = 1,2,\ldots,Q\} \) by processing the columns of the matrix (7), whose elements depend on \( \ell_u \), and to estimate \( \{r_{1}^{q_p}, \theta_{1}^{q_p}\}|p = 1,2,\ldots,P, q = 1,2,\ldots,Q\} \) by processing the rows of the matrix (7), whose elements depend on \( k_w \). To ensure the accuracy of OAM-based target imaging, we assume that \( U \geq QP \) and \( W \geq QP \). Eventually, the estimates of \( \{\theta_{1}^{q_p}, \varphi_{1}^{q_p}\} \) in the OAM mode domain can be combined with the estimates of \( \{r_{1}^{q_p}, \theta_{1}^{q_p}\} \) in the frequency domain to obtain the 3-D positions of all the scattering points.

2) Estimation in OAM Mode Domain: The MUSIC algorithm, a subspace-based super-resolution algorithm, provides an elegant means for estimating the parameters of complex sinusoidal signals embedded in white Gaussian noise [41]. In the estimation of \( \theta_{1}^{q_p} \) and \( \varphi_{1}^{q_p} \), we first denote the \( w \)-th column of \( E_R^{'} \) as a column vector \( e_w \), i.e.,
\[
e_w = E_R^{'}(:,w) = [E_R^{'}(\ell_1, k_w), E_R^{'}(\ell_2, k_w), \cdots, E_R^{'}(\ell_U, k_w)]^T,
\]
so that \( e_w \) can be expressed in compact form as
\[
e_w = A_w s_w + n_w, \quad (8)
\]
where \( A_w = [e^{i\ell_u \varphi_{1}^{q_p}} J_0(k_w R \sin \theta_{1}^{q_p})]_{U \times QP} \) is the direction matrix containing angle information of all the scattering points, \( s_w = \Sigma_w \sigma_s, \Sigma_w = \text{diag} \{J_0(k_w R \sin \theta_{1}^{q_p}) e^{i2k_w r_{1}^{q_p}}, \cdots, J_0(k_w R \sin \theta_{1}^{q_p}) e^{i2k_w r_{1}^{q_p}}\} \), \( \sigma_s = [\sigma_{u_1}, \cdots, \sigma_{Q_P}]^T \), and \( n_w \) is the noise vector. In practice, the OAM echo signals from different scattering points are usually incoherent, i.e.,
\[
\mathbb{E} \{\sigma_{q_p}^{*} \sigma_{q_p}'\} = \begin{cases} \mathbb{E} \{\sigma_{q_p}^{*} \sigma_{q_p}'\}, & q_p = q_p' \\ 0, & q_p \neq q_p' \end{cases} \quad (9)
\]

Then, the covariance matrix of \( e_w \) can be written as
\[
R_e_w = \mathbb{E} \{e_w e_w^H\} = A_w R_s A_w^H + R_{n_w}, \quad (10)
\]
where \( R_s = \Sigma_w \mathbb{E} \{\sigma_s \sigma_s^H\} \Sigma_w^H, R_{n_w} = \mathbb{E} \{n_w n_w^H\}. \) The eigen value decomposition (EVD) of \( R_{e_w} \) is
\[
R_{e_w} = \sum_{u=1}^{U} \lambda_{u,w} q_{u,w} q_{u,w}^H = Q_u A_u Q_u^H, \quad (11)
\]
where \( \{\lambda_{u,w}|u = 1,2,\ldots,U\} \) are the eigenvalues of \( R_{e_u} \), \( A_u = \text{diag} \{\lambda_1, \lambda_2, \ldots, \lambda_U, 0, \ldots\} \), \( q_{u,w} \) is the eigenvector corresponding to the eigenvalue \( \lambda_{u,w} \) and \( Q_u = [Q_{1,w}, \cdots, Q_{U,w}] \).

In practice, the echo signals and noise are independent of each other, thus, the covariance matrix \( R_{e_w} \) can be decomposed into two mutually orthogonal parts:
\[
R_{e_w} = Q_u A_u q_{u,w} q_{u,w}^H + Q_{n_w} A_{n_w} q_{n_w}^H, \quad (12)
\]
where \( A_u^* \) is the \( QP \)-dimensional diagonal matrix containing the larger QP eigenvalues of \( R_{e_u} \), \( Q_u^* \) is the \( U \times QP \) signal subspace composed of the eigenvectors corresponding to the larger QP eigenvalues, \( A_{n_w}^* \) is the \( (U - QP) \)-dimensional diagonal matrix containing the smaller \( U - QP \) eigenvalues of \( R_{e_u} \), \( Q_{n_w}^* \) is the \( U \times (U - QP) \) noise subspace composed of the eigenvectors corresponding to the smaller \( U - QP \) eigenvalues. Based on (10) and (12), we can see that
\[
R_{e_w} Q_{n_w}^* = A_u R_{s_w} A_w Q_{n_w}^* + R_{n_w} Q_{n_w}^* = R_{n_w} Q_{n_w}^*, \quad (13)
\]
i.e., $A_w R_w A_H^w Q_w^n = 0$. Since $R_w = \Sigma_w E\{\sigma, \sigma^H\} \Sigma_W^H$ is a full rank matrix, which must be reversible, $A_H^w Q_w^n = 0$, that is, the direction matrix $A_w$ is orthogonal to the noise subspace $Q_w^n$.

Based on the orthogonality between $A_w$ and $Q_w^n$, the spatial-spectral function can be constructed as

$$P_{w}(\theta_{t}, \varphi_{t}) = \frac{1}{a_{w}(\theta_{t}, \varphi_{t})} W_{w}(\theta_{t}, \varphi_{t}) A_{w}^H A_{w}(\theta_{t}, \varphi_{t}),$$

(14)

where $a_{w}(\theta_{t}, \varphi_{t}) = e^{j \theta_{t} \sin \theta_{t}} J_{\ell_{1}}(k_{u} R \sin \theta_{t})$, $e^{j \theta_{t} \sin \theta_{t}} J_{\ell_{2}}(k_{u} R \sin \theta_{t})$, ..., $e^{j \theta_{t} \sin \theta_{t}} J_{\ell_{w}}(k_{u} R \sin \theta_{t})$. Then, the estimates $\{(\hat{\theta}_{w} u, \hat{\varphi}_{w} u)\}$ can be obtained through the 2-D spectrum peak searching in (14).

Hence, there are $W$ estimates of $\{(\hat{\theta}_{w} u, \hat{\varphi}_{w} u)\}$ in total, which can be expressed as

$$\hat{\theta}_{w} u = \theta_{w} + \varepsilon_{\theta_{w} u}, \quad \hat{\varphi}_{w} u = \varphi_{w} + \varepsilon_{\varphi_{w} u},$$

(15)

where $\varepsilon_{\theta_{w} u}$ and $\varepsilon_{\varphi_{w} u}$ represent the estimation errors, $p = 1, 2, \ldots, P$, $q = 1, 2, \ldots, Q$, $w = 1, 2, \ldots, W$. Suppose that $\varepsilon_{\theta_{w} u} \sim \mathcal{N}(0, \sigma_{\theta_{w} u}^2)$ and $\varepsilon_{\varphi_{w} u} \sim \mathcal{N}(0, \sigma_{\varphi_{w} u}^2)$, then the column of $Q_w$ corresponding to $A_w$ can be obtained as

$$\hat{\theta}_{w} u = \hat{\theta}_{w} u + \frac{1}{W} \sum_{w=1}^{W} \hat{\varphi}_{w} u,$$

(16)

as the estimate of $\varphi_{w}$.

3) Estimation in Frequency Domain: In the estimation of $r_{t}^{q}$ and $\hat{\theta}_{t}^{q}$, we similarly denote the $u$-th row of $E_{R}^{u}$ as a column vector $e_{u}$, i.e.,

$$e_{u} = E_{R}^{u}(u, \cdot) = [E_{R}^{u}(u, k_{1}), E_{R}^{u}(u, k_{2}), \ldots, E_{R}^{u}(u, k_{W})]^T,$$

so that $e_{u}$ can be expressed in compact form as

$$e_{u} = B_{u} s_{u} + n_{u},$$

(17)

where $B_{u} = \left[e^{j k_{u} r_{t}^{q}} J_{\ell_{1}}(k_{u} R \sin \theta_{t}^{q}) J_{0}(k_{u} R \sin \theta_{t}^{q}) \right]_{W \times Q_{P}}$ is the position matrix containing 2-D position information of all the scattering points, $s_{u} = \Sigma u \sigma_{u}$, $\Sigma_{u} = \sum_{\ell_{1}} \sum_{\ell_{2}} \ldots \sum_{\ell_{w}}$, and $n_{u}$ is the noise vector. Then, by computing the correlation matrix $R_{e_{u}} = E\{e_{u} e_{u}^H\}$ and, following the same method outlined in the previous section, we can obtain the estimates $\{(\hat{r}_{t}^{q u}, \hat{\theta}_{t}^{q u})\}$ by

$$\hat{r}_{t}^{q u} = \frac{1}{U} U \sum_{u=1}^{U} \hat{r}_{t}^{q u},$$

(18)

and

$$\hat{\theta}_{t}^{q u} = \frac{1}{U + W} \left( W \sum_{u=1}^{W} \hat{\theta}_{t}^{q u} + U \sum_{u=1}^{U} \hat{\theta}_{t}^{q u} \right).$$

(19)

The detailed procedure to obtain the 3-D estimated position $(\hat{r}_{t}^{q u}, \hat{\theta}_{t}^{q u}, \hat{\varphi}_{t}^{q u})$ of $q$-th target is summarized in Algorithm 1. The proposed MUSIC-based imaging algorithm performs a 2-D search for the amplitude and phase of OAM echo signals in the frequency and OAM mode domains, respectively, thus realizing the 3-D super-resolution position estimation of multiple targets without beam scanning.

Algorithm 1 OAM-Based 3-D Position Estimation

Input: $E_{R}^{u}$

Output: $\{(\hat{r}_{t}^{q u}, \hat{\theta}_{t}^{q u}, \hat{\varphi}_{t}^{q u})\}$, $p = 1, 2, \ldots, P$, $q = 1, 2, \ldots, Q$

1: procedure
2: $e_{u} \leftarrow E_{R}^{u}(u, \cdot), w = 1, 2, \ldots, W$
3: $R_{e_{u}} \leftarrow E\{e_{u} e_{u}^H\}, w = 1, 2, \ldots, W$
4: for $w = 1 \rightarrow W$ do
5: $Q_{w}, A_{w} \leftarrow$ decompose $R_{e_{w}}$ such that $Q_{w} A_{w} H_{w}^n$
6: $A_{w} \leftarrow \text{diag}\{\lambda_{w 1}, \ldots, \lambda_{w W}\}$, $\lambda_{w 1} \geq \cdots \geq \lambda_{w P_{w}}$
7: $A_{w}^n \leftarrow \text{diag}\{\lambda_{w Q_{p}+1}, \ldots, \lambda_{w W}\}$
8: $Q_{w}^n \leftarrow$ the column of $Q_{w}$ corresponding to $A_{w}^n$
9: $a_{w}(\theta_{t}, \varphi_{t}) = e^{j \theta_{t} \sin \theta_{t}} J_{\ell_{1}}(k_{u} R \sin \theta_{t})$
10: $P_{w}(\theta_{t}, \varphi_{t}) = 1/(a_{w}^H(\theta_{t}, \varphi_{t}) Q_{w} A_{w}^H A_{w}(\theta_{t}, \varphi_{t}))$
11: $(\hat{\theta}_{w} u, \hat{\varphi}_{w} u) \leftarrow$ 2-D spectrum peak searching in $P_{w}(\theta_{t}, \varphi_{t})$
12: end for
13: $\hat{\varphi}_{t}^{q u} = \frac{1}{W} \sum_{w=1}^{W} \hat{\varphi}_{w} u, p = 1, \ldots, P$, $q = 1, \ldots, Q$
14: $e_{u} \leftarrow E_{R}^{u}(u, \cdot), u = 1, 2, \ldots, U$
15: $R_{e_{u}} \leftarrow E\{e_{u} e_{u}^H\}, u = 1, 2, \ldots, U$
16: for $u = 1 \rightarrow U$ do
17: $Q_{u}, A_{u} \leftarrow$ decompose $R_{e_{u}}$ such that $Q_{u} A_{u} U_{H}^u$
18: $A_{u} \leftarrow \text{diag}\{\lambda_{u 1}, \ldots, \lambda_{u W}\}$, $\lambda_{u 1} \geq \cdots \geq \lambda_{u Q_{P}}$
19: $A_{u}^n \leftarrow \text{diag}\{\lambda_{u Q_{p}+1}, \ldots, \lambda_{u W}\}$
20: $Q_{u}^n \leftarrow$ the column of $Q_{u}$ corresponding to $A_{u}^n$
21: $b_{u}(r_{t}, \theta_{t}) = [a_{u}^{\ell_{1}}, a_{u}^{\ell_{2}}, \ldots, a_{u}^{\ell_{w}}], n_{u}^{H}(k_{u} R \sin \theta_{t})$
22: $P_{u}(r_{t}, \theta_{t}) \leftarrow 1/(b_{u}^H(r_{t}, \theta_{t}) Q_{u}^n b_{u}(r_{t}, \theta_{t}))$
23: $(\hat{r}_{t}^{q u}, \hat{\theta}_{t}^{q u}) \leftarrow$ 2-D spectrum peak searching in $P_{u}(r_{t}, \theta_{t})$
24: end for
25: $r_{t}^{q u} = \frac{1}{U} \sum_{u=1}^{U} \hat{r}_{t}^{q u}, p = 1, \ldots, P$, $q = 1, \ldots, Q$
26: $\hat{\varphi}_{t}^{q u} = \frac{1}{U + W} \left( W \sum_{u=1}^{W} \hat{\varphi}_{t}^{q u} + U \sum_{u=1}^{U} \hat{\varphi}_{t}^{q u} \right), p = 1, \ldots, P$, $q = 1, \ldots, Q$
27: end procedure

B. OAM-Based Rotation Velocity Detection

1) Problem Formulation: The precession characteristic of targets is the key basis for distinguishing the type of targets [42], [43]. In the scenario shown in Fig. 1, the targets are moving along the trajectory while rotating around their axis, and the rotation velocity is an important precession parameter. In this paper, we will focus on the OAM-based rotation velocity detection to lay a foundation for distinguishing the type of targets.

For easier understanding, we take the vertex $V_{q}$ of $q$-th target as an example to derive the theoretical expression of the rotation velocity. The motion state of the $q$-th target
Fig. 3. The diagram of the OAM-based rotation velocity detection.

is shown in Fig. 3, whose centroid at time instant \( t \) has coordinates \( (\rho_t^0, \theta_t^0, \varphi_t^0) \). The \( q \)-th target is moving in the direction \( \rho_t^q \) at a velocity \( v_t^q \) while rotating around the \( \text{OP}_q \)-axis at an angular velocity \( \Omega_t^q \). Suppose the rotation center of \( V_q \) is \( \text{O}_q \) and the rotation radius is \( \gamma_t^q \), the vector \( \text{O}_q V_q \) can be written as

\[
\text{O}_q V_q = \left( \frac{x_t^q}{y_t^q}, \frac{y_t^q}{z_t^q} \right) = R_{\text{ro}} \cdot \left( \begin{array}{c} \gamma_t^q \cos(\Omega_t^q t + \psi_t^q) \\ \gamma_t^q \sin(\Omega_t^q t + \psi_t^q) \\ 0 \end{array} \right), \quad (20)
\]

where

\[
R_{\text{ro}} = \begin{bmatrix}
\cos \varphi_t^0 & -\sin \varphi_t^0 & 0 \\
\sin \varphi_t^0 \sin \theta_t^0 & \cos \varphi_t^0 \cos \theta_t^0 & -\sin \theta_t^0 \\
\sin \varphi_t^0 \cos \theta_t^0 & \cos \varphi_t^0 \sin \theta_t^0 & \cos \theta_t^0
\end{bmatrix}
\]

is the rotation matrix determined by the the position of the \( q \)-th target and \( \psi_t^q \) is the initial azimuth angle of the vertex \( V_q \). When \( V_q \) rotates around \( \text{OP}_q \)-axis, the corresponding linear velocity vector \( v_v \) is perpendicular to \( \text{OP}_q \) and \( \text{O}_q V_q \), thus, the linear velocity vector \( v_v \) can be expressed as

\[
v_v = (v_t^x, v_t^y, v_t^z) = \text{O}_q V_q = (y_t^q z_t^q - z_t^q y_t^q, z_t^q x_t^q - x_t^q z_t^q, x_t^q y_t^q - y_t^q x_t^q),
\]

where \( \rho_t^0 = \frac{\rho_t^q}{\rho_t^0} \) is the moving distance of \( C_q \) while rotating around the \( \text{OP}_q \), then, within the period \( \Delta t \), the moving distance of \( C_q \) that is the projection of the vertex \( V_q \) in the XOY-plane can be expressed as

\[
\Delta d_t^{qV} = (v_v \cdot \hat{r}_t^{qV}) \Delta t = \frac{-y_t^0 v^z_t + x_t^0 v^y_t}{\sqrt{(x_t^0)^2 + (y_t^0)^2}} \Delta t
\]

\[
\Delta d_t^{qV} = -\frac{y_t^0}{\sqrt{(x_t^0)^2 + (y_t^0)^2}} \cdot \hat{r}_t^{qV} \Delta t
\]

\[
\Delta d_t^{qV} = \frac{1}{\sqrt{(x_t^0)^2 + (y_t^0)^2}} \cdot \hat{r}_t^{qV} \Delta t
\]

where \( \hat{r}_t^{qV} = \frac{1}{\sqrt{(x_t^0)^2 + (y_t^0)^2}} \cdot \hat{r}_t^{qV} \) is the unit vector on the XOY-plane projected by the vector perpendicular to \( \text{OP}_q \), \( \delta_q^0 = \arctan(\cos \varphi_t^0 \sin \theta_t^0 / \sin \varphi_t^0) \). After that, the change of the azimuth angle of the vertex \( V_q \) can be expressed as

\[
\Delta \varphi_t^{qV} = \lim_{\Delta t \to 0} \frac{\Delta d_t^{qV}}{|\text{OC}_q|}.
\]

With (23), we can derive the theoretical rotational Doppler shift of the vertex \( V_q \) induced by azimuthal change.

Based on (6), the phase term of the OAM echo signal of the vertex \( V_q \) on the \( u \)-th mode at the \( w \)-th subcarrier can be written as

\[
\Phi_t^{qV}(u, k_w) = 2\pi \rho_t^{qV} + \varphi_t^{qV}.
\]

Thus, the Doppler shift of the vertex \( V_q \) can be expressed as

\[
f_t^{qV}(u, k_w) = \frac{1}{2\pi} \frac{d \Phi_t^{qV}(u, k_w)}{dt} = f_L^{qV}(k_w) + f_{\Omega}^{qV}(u),
\]

where

\[
f_L^{qV}(k_w) = \frac{1}{2\pi} k_w v_t^{qV} \cos \rho_t^{qV}
\]

is the linear Doppler shift induced by distance variation, and

\[
f_{\Omega}^{qV}(u) = \frac{\ell_u}{2\pi} \lim_{\Delta t \to 0} \frac{\Delta \varphi_t^{qV}}{\Delta t} = \frac{\ell_u}{2\pi} g_t^{qV} \Omega_t^{qV} \cos(\Omega_t^{qV} t + \psi_t^{qV} + \delta_q^0),
\]

is the rotational Doppler shift induced by azimuthal change, and

\[
g_t^{qV} = \frac{-\gamma_t^q \sqrt{\sin^2 \varphi_t^0 + \cos^2 \varphi_t^0 \sin^2 \theta_t^0}}{(\gamma_t^q - \gamma_t^0) \sin \theta_t^0}.
\]

From (27), we can observe that the rotational Doppler shift of \( V_q \) is frequency independent and determined only by the
OAM mode number \( \ell_u \) and angular velocity \( \Omega^q_{t,u} \), so that the higher the OAM mode is, the larger is the rotational Doppler shift. In the next part, we will discuss in detail how to extract the rotational Doppler shift of each scattering point from (6) and obtain the angular velocity \( \Omega^q_{t,u} \).

2) Detection of \( \Omega^q_{t,u} \): The rotation of a rigid body is essentially a kind of non-uniform motion. Thus, the echo signals are non-linear and non-stationary [25]. The core problem of extracting and analyzing the rotational Doppler shift of each scattering point from (6) is the processing of time-varying signals. Due to its suitability for non-stationary signal analysis, the STFT method has long been used for Doppler imaging [25], [44]. After time-frequency processing of the OAM echo signal \( E^q_{t,u}(\ell_u, k_w) \), we can obtain the time-frequency distribution of each scattering point superposed by the linear Doppler shift and the rotational Doppler shift. Then, inspired by the work in [25], the OAM echo signals \( \{ E^q_{t,u}(0, k_w) \}_{|w = 1, 2, \cdots, W} \) are utilized to separate the linear and rotational Doppler shifts, and the time-frequency distribution of the \( q_p \)-th scattering point only consisting of the rotational Doppler shift can be expressed as

\[
\bar{f}^q_{D,\ell} (\ell_u) = f^q_{D,\ell} (\ell_u, k_w) - f^q_{D,\ell} (0, k_w), \quad \ell_u \neq 0.
\]

After that, the rotation period \( T_{q_p}^{\ell_u} \) of \( q_p \)-th scattering point can be obtained from the time-frequency distribution of \( \bar{f}^q_{D,\ell} (\ell_u) \), and the angular velocity can be calculated as \( \hat{\Omega}_{t,u}^q = 2\pi/T_{q_p}^{\ell_u} \).

Hence, there are \( U-1 \) estimates of \( \Omega^q_{t,u} [p = 1, 2, \cdots, P, q = 1, 2, \cdots, Q] \) in total, which can be expressed as

\[
\tilde{\Omega}_{t,u}^q = \Omega^q_{t,u} + \varepsilon_{t,u}^q,
\]

where \( \varepsilon_{t,u}^q \) represents the estimation errors, \( p = 1, 2, \cdots, P, q = 1, 2, \cdots, Q, u = 1, 2, \cdots, U-1 \). Suppose that \( \{ \varepsilon_{t,u}^q \}_{u = 1, 2, \cdots, U-1} \) have the same average variance \( \text{Var}(\varepsilon_{t,u}^q) \), thus,

\[
\text{Var} \left( \frac{1}{U-1} \sum_{u=1}^{U-1} \tilde{\Omega}_{t,u}^q \right) = \text{Var}(\varepsilon_{t,u}^q) / (U-1).
\]

Therefore, \( \hat{\tilde{\Omega}}_t^q = \frac{1}{U-1} \sum_{u=1}^{U-1} \tilde{\Omega}_{t,u}^q \) is adopted as the estimate of \( \Omega_t^q \), and the detailed procedure is summarized in Fig.4. It should be noted that the detected rotation velocity of the scattering points in the same target should be the same, except that at the centroid of the target, its rotation velocity is detected as zero since its rotation Doppler shift is zero.

Thus, OAM-based rotating target imaging is completed. In the numerous estimated parameters, the 3-D estimated positions \( \{(t_1, \hat{\theta}_1^q, \hat{\varphi}_1^q)\}_{q = 1, 2, \cdots, Q} \) of the centroid of each target and the rotation velocities \( \{\Omega_t^q\}_{q = 1, 2, \cdots, Q} \) of the vertex of each target are regarded as the most important estimated parameters, which represent the key state characteristic of each target at time instant \( t \).

IV. BEAM OPTIMIZATION OF JOINT OAM RADAR-COMMUNICATION SYSTEM

In the following part, we will first analyze the performances of the proposed radar-centric joint OAM RadCom system, and then optimize the transmitted integrated OAM beams to achieve the best trade-off between the imaging and communication performances of the system.

A. PCRB of OAM-Based Target Imaging

In this subsection, we discuss the PCRB of key state parameters \( \{(r_1^q, \theta_1^q, \varphi_1^q, \Omega_t^q, \Omega_q^1)\}_{q = 1, 2, \cdots, Q} \) of \( Q \) targets, which is regarded as the important metric for imaging performance [45]. First, all the key state parameters to be estimated are collected in

\[
\vartheta = [r_1^1, \theta_1^1, \varphi_1^1, \Omega_t^1, \Omega_1^1, \cdots, r_1^Q, \theta_1^Q, \varphi_1^Q, \Omega_t^Q, \Omega_q^Q]^T.
\]

To derive the PCRB, the OAM echo signal received on the \( u \) mode at the \( w \) subcarrier in (4) is rewritten as

\[
E^q_{t,u}(\ell_u, k_w) = p(\ell_u, k_w, \vartheta) + n(\ell_u, k_w),
\]

where

\[
p(\ell_u, k_w, \vartheta) = -j \frac{A_w \mu_0 \omega_u d^2}{4\pi} \left[ \sum_{p=1}^{P} \sum_{q=1}^{Q} \sigma_{e^q_{p,w}} e^{j2\pi k_w r_{e^q_{p,w}}} e^{j\ell_u \varphi_{e^q_{p,w}}} J_t(k_w R \sin \theta_{e^q_{p,w}}) \right] \\
\times J_0(k_w R \sin \theta_{e^q_{p,w}}).
\]

Then, all the OAM echo signals received on the \( U \) modes at the \( W \) subcarriers can be expressed in compact form as

\[
E_R = P(\vartheta) + N,
\]

where \( E_R = \{ E^q_{t,u}(\ell_u, k_w) \}_{U \times W} \), \( P(\vartheta) = [p(\ell_u, k_w, \vartheta)]_{U \times W} \), and \( N = [n(\ell_u, k_w)]_{U \times W} \).

After that, the Fisher information matrix \( J \) [45] with respect to \( \vartheta \) can be expressed in (33), shown at the bottom of the next page, whose detailed derivation is given in Appendix. Based on (33), the PCRB of the key state parameter to be estimated in \( \vartheta \) can be expressed as

\[
\text{E} \{ (\hat{\vartheta}_i - \vartheta_i)^2 \} \geq [J^{-1}]_{ii},
\]

where \( \hat{\vartheta}_i \) is the i-th key state parameter in \( \vartheta \), \( \vartheta_i \) is the estimate of \( \vartheta_i \), and \( [J^{-1}]_{ii} \) is the i-th diagonal element of the inverse matrix of \( J \).

B. Spectral Efficiency of Joint OAM RadCom System

In this subsection, we discuss the SE of the radar-centric joint OAM RadCom system based on (5). During a period, the equivalent baseband signal vector \( y_q(k_w) \) received by the specific target at the \( w \)-th subcarrier can be expressed as

\[
y_q(k_w) = H_q(k_w) X(k_w) + z_q(k_w)
\]

\[
= H_q(k_w) F A S(k_w) + z_q(k_w),
\]

where \( y_q(k_w) = [y_q(\ell_u, k_w)]_{1 \times U} \) and \( y_q(\ell_u, k_w) \) is given by (5), \( H_q(k_w) = [h^q_{n,w}(k_w)]_{1 \times M} \) is the channel matrix from the dual-function transmitter to the specific target, \( X(k_w) = [A_w e^{j2\pi \omega_u s(\ell_u, k_w)}]_{M \times U} \) is the transmit signal matrix generated by the dual-function transmitter,
\[ F = \left[ e^{j \ell_{u} \varphi_{m}} \right]_{M \times U} \] is the right circularly shifted (partial) inverse fast Fourier transform (IFFT) matrix used to generate integrated OAM beams, \( A = \text{diag}\{ A_1, \cdots, A_w \} \) is the \( U \)-dimensional weight matrix of the integrated OAM beams, \( S(k_{w}) = \text{diag}\{ s(\ell_{1}, k_{w}), \cdots, s(\ell_{U}, k_{w}) \} \) is the \( U \)-dimensional integrated OAM symbol matrix at the \( w \)-th subcarrier, and \( z_{q}(k_{w}) = [z(\ell_{1}, k_{w}), \cdots, z(\ell_{U}, k_{w})] \) is the noise vector.

In the proposed radar-centric joint OAM RadCom system, we assume to detect the received OAM signals by employing the simplest zero-forcing detection method. Then, after obtaining the channel state information (CSI) by the parametric channel estimation method [32, 33, 34], the detected data symbol matrix at the specific target can be expressed as

\[
\hat{S}_{q}(k_{w}) = (\hat{H}_{q}(k_{w}) F) \text{Diag}(q) (\hat{S}(k_{w}) + z_{q}(k_{w}))
\]

\[
= AS(k_{w}) + I_q(k_{w}) + \hat{Z}_{q}(k_{w}),
\]

where \( \hat{H}_{q}(k_{w}) \) is the estimated channel matrix, \( I_q(k_{w}) = ((\hat{H}_{q}(k_{w}) F) (\hat{H}_{q}(k_{w}) F-I_{U})) AS(k_{w}) \) is the remaining interferences induced by the error in \( \hat{H}_{q}(k_{w}) \), \( I_{U} \) is the \( U \)-dimensional unit matrix, \( \hat{Z}_{q}(k_{w}) = (\hat{H}_{q}(k_{w}) F) z_{q}(k_{w}) \).

Define \( R_{AS}^{q}(k_{w}), R_{I}^{q}(k_{w}) \) and \( R_{Z}^{q}(k_{w}) \) as the \( U \times U \) covariance matrices of \( AS(k_{w}), I_q(k_{w}) \) and \( \hat{Z}_{q}(k_{w}) \), i.e.,

\[
R_{AS}^{q}(k_{w}) = A E \left\{ S(k_{w}) S^H(k_{w}) \right\} A^H,
\]

\[
R_{I}^{q}(k_{w}) = ((\hat{H}_{q}(k_{w}) F) (\hat{H}_{q}(k_{w}) F-I_{U})) A E \left\{ S(k_{w}) S^H(k_{w}) \right\} A^H ((\hat{H}_{q}(k_{w}) F) (\hat{H}_{q}(k_{w}) F-I_{U}))^H,
\]

\[
R_{Z}^{q}(k_{w}) = (\hat{H}_{q}(k_{w}) F) E \left\{ z_{q}(k_{w}) z_{q}^H(k_{w}) \right\} ((\hat{H}_{q}(k_{w}) F))^H,
\]

then, the signal-to-interference-plus-noise ratio (SINR) on the \( w \)-th OAM mode at the \( w \)-th subcarrier can be formulated as

\[
\text{SINR}_{q}(\ell_{u}, k_{w}) = \frac{R_{AS}^{q}(k_{w})_{uu}}{R_{I}^{q}(k_{w})_{uu} + R_{Z}^{q}(k_{w})_{uu}}.
\]

where \([ ]_{uu}\) is the \( u \)-th diagonal element of the matrix. Therefore, the average SE at the specific communication target during each period can be written as

\[
C_{av}^{q} = \frac{1}{U} \sum_{w=1}^{W} \sum_{u=1}^{U} \log_{2} (1 + \text{SINR}_{q}(\ell_{u}, k_{w})).
\]

C. Optimization of Integrated OAM Beams

From (34) and (39), we can see that both the imaging and communication performances of the joint OAM RadCom system are closely associated with the weights.
\{A_u | u = 1, 2, \ldots, U\} of integrated OAM beams. Different power distribution schemes will directly affect the performance of the system. To achieve the best trade-off between the imaging and communication performances, we formulate the optimization problem to minimize the PCRB, subject to the SE constraint for the specific target as well as a transmit power budget, i.e.,

$$\min_{A_1, \ldots, A_U} \sum_{i=1}^{4Q} [J^{-1}]_{ii}$$

s.t. \[C^u_{av} \geq C^\min_{av}, \sum_{u=1}^{4Q} |A_u|^2 = 1, \] (40)

where \(C^\min_{av}\) is the minimum average SE required by the specific target.

Since \(\sum_{i=1}^{4Q} [J^{-1}]_{ii}\) can not be expressed as a function of \(\theta\) in the closed form, we propose to solve the optimization problem (40) by the exhaustive search method, which is the simplest optimization method [46]. In the exhaustive search method, the optimal value of the problem (40) can be obtained by calculating the function values at several equally spaced points. We first select a search step size \(\Delta = 1/9\bar{\Omega}\), for the weight \(A_u \in (0, 1)\), and calculate the function values of all search points \(\{A^n_u | n_u = 1, 2, \ldots, N, u = 1, 2, \ldots, U\}\) based on the problem (40), where \(\bar{\Omega}\) is the number of intermediate points, \(A^n_{u}\) is the \(n_u\)-th intermediate point of the weight \(A_u\). According to the calculation result, the search point \(\{A^n_{u} | u = 1, 2, \ldots, U\}\) that minimizes the PCRB and meets the constraints is adopted as the optimal value of the problem (40), and the detailed procedure is summarized in Fig.5. Based on the optimal weights, the dual-function transmitter distributes power for \(U\) integrated OAM beams in a period to achieve the best performance trade-off of the radar-centric joint OAM RadCom system.

V. NUMERICAL Simulations AND RESULTS

In this section, we show the performances of the proposed scheme by numerical simulations. We first verify the proposed OAM-based 3-D position estimation and rotation velocity detection methods at different signal-to-noise ratios (SNRs), and compare the mean square error (MSE) of the proposed methods with the PCRB of the OAM-based imaging. Then, we plot the PCRB and SE of the radar-centric joint OAM RadCom system vs. the SNR. Finally, we show the performance trade-off under the different SE constraints. Unless otherwise stated, the SNRs in all the figures are defined as the ratio of the transmitted signal power versus the noise power.

We choose \(W = 16\) subcarriers from 9.979GHz to 10.695GHz corresponding to the wave numbers \(k_1, k_2, \ldots, k_{16} = 209, 210, \ldots, 224\), \(M = N = 17\), \(U = 16\) OAM modes with \(\ell_1, \ell_2, \ldots, \ell_{16} = -8, -7, \ldots, +7\), \(R = 30\lambda_1\), \(\lambda_1 = 2\pi/k_1\), \(Q = 3\) with the key state parameters of the specific communication target \((r^{1u}, \theta^{1u}, \varphi^{1u}, \Omega^{1u})\) = (82.5m, 20°, 70°, 8π) and other targets \((r^{20}, \theta^{20}, \varphi^{20}, \Omega^{20})\) = (170m, 80°, 20°, 10π), \((r^{30}, \theta^{30}, \varphi^{30}, \Omega^{30})\) = (165m, 75°, 25°, 11.5π) and \(P = 3\) scattering points per target.

Then, by using the proposed method, the estimated positions of \(Q\) targets are shown in Fig.6. As we can see from the figure, the estimated positions of \(Q\) targets approach the actual positions as the SNR increases, e.g., when SNR reaches 20dB, it is \((r^{1u}, \theta^{1u}, \varphi^{1u}) = (82.502m, 19.997°, 69.995°), (r^{20}, \theta^{20}, \varphi^{20}) = (169.996m, 80.002°, 19.998°), (r^{30}, \theta^{30}, \varphi^{30}) = (165.000m, 74.996°, 24.994°)\), which are very close to the actual positions.

Fig.7 shows the time-frequency distributions of the vertices of \(Q\) targets. It can be seen the theoretical curves almost coincide with the time-frequency simulation results, proving the effectiveness of the rotational Doppler shift model derived in Section III.B. Thereafter, the estimated rotation velocities are shown in Table I. The estimated measures approach the actual velocities as the SNR increases. Meanwhile, noise has little influence on the rotation velocity detection when using the STFT method.

**TABLE I**

| \(\hat{\Omega}^{1\nu}_l\) | \(\hat{\Omega}^{2\nu}_l\) | \(\hat{\Omega}^{3\nu}_l\) |
|-----------------|-----------------|-----------------|
| 5dB | 8.281π | 10.225π | 11.961π |
| 10dB | 7.861π | 10.163π | 11.720π |
| 15dB | 8.045π | 9.901π | 11.628π |
| 20dB | 8.000π | 10.004π | 11.495π |

Fig 5. The flowchart of the weight optimization of integrated OAM beams with the exhaustive search method.
In Fig. 8, we compare the MSEs and PCRBs of the estimates \( \{(\hat{r}_q^0, \hat{\theta}_q^0, \hat{\phi}_q^0, \hat{\Omega}_q^{1\nu})\}_{q = 1, 2, 3} \) under the condition of average power distribution. The MSE is defined as \( \mathbb{E}\{(\hat{x} - x)^2\} \), where \( \hat{x} \) denotes the estimate of \( x \). As the SNR increases, the MSEs of the estimates decrease and approach the PCRBs gradually. At high SNRs, the MSEs of the estimates \( \{(\hat{r}_q^0, \hat{\theta}_q^0, \hat{\phi}_q^0, \hat{\Omega}_q^{1\nu})\}_{q = 1, 2, 3} \) are very close to their PCRBs, proving the effectiveness of the proposed OAM-based rotating target imaging method.

After that, the PCRBs and SE of the radar-centric joint OAM RadCom system are simulated under QPSK modulation. An example of the system performance under a random power allocation with \( A_1 = 0, A_2 = 0.071, A_3 = 0.354, A_4 = 0.554, A_5 = 0.283, A_6 = 0.141, A_7 = 0.141, A_8 = 0.283, A_9 = 0.3, A_{10} = 0.283, A_{11} = 0.141, A_{12} = 0.141, A_{13} = 0.283, A_{14} = 0.354, A_{15} = 0.354, A_{16} = 0.071 \) is shown in Fig. 9 (b), whose PCRBs are superior to those under the average power distribution shown in Fig. 9 (a), verifying...
Fig. 8. The comparison of the MSEs and PCRBs. (a) Specific communication target \((\hat{r}_1, \hat{\theta}_1, \hat{\phi}_1, \hat{\Omega}_1)\). (b) Other target 1 \((\hat{r}_2, \hat{\theta}_2, \hat{\phi}_2, \hat{\Omega}_2)\). (c) Other target 2 \((\hat{r}_3, \hat{\theta}_3, \hat{\phi}_3, \hat{\Omega}_3)\).

Based on the simulation results of SE in Fig. 9, we assume that the SEs required by the specific target are 6 bit/s/Hz in Fig. 10 (a) and 7 bit/s/Hz in Fig. 10 (b), the transmit SNR is 15dB, and the number of intermediate points is \(N = 10\). It can be seen from Fig. 10 that under different SE constraints, the PCRBs of the system have different optimization results. More importantly, comparing Fig. 9 and Fig. 10, we can see that by using the proposed optimization method, the PCRBs of the joint OAM RadCom system are greatly improved while the SEs of the specific target are guaranteed, realizing the best performance trade-off of the system.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

In this paper, we propose a novel UCA-based radar-centric joint OAM RadCom scheme including the OAM-based 3-D position estimation, rotation velocity detection and specific target communication. In terms of the OAM-based position estimation, we propose a 3-D super-resolution position estimation method based on the MUSIC algorithm. By performing
the 2-D search for the amplitude and phase of OAM echo signals in the frequency and OAM mode domains respectively, the proposed imaging method realizes the 3-D super-resolution imaging of multiple targets without beam scanning. Moreover, we discuss a rotation velocity detection method based on the STFT algorithm, which takes full advantage of the rotational Doppler characteristics of OAM echo signals to estimate the rotation velocities of multiple targets simultaneously, providing a basis for distinguishing the type of targets. Thereafter, we analyze the PCRB and SE of the radar-centric joint OAM RadCom system, and then optimize the transmitted integrated OAM beams by applying an exhaustive search method to achieve an optimal performance trade-off. Both mathematical analysis and simulation results show that the proposed radar-centric joint OAM RadCom scheme can accurately estimate the 3-D position and rotation velocity of multiple targets, while ensuring the SE of the specific target.

### B. Future Work

To simplify the beam optimization method, it is essential to quantitatively analyze the imaging and communication performances of the radar-centric joint OAM RadCom system, which is left for our future work. Moreover, the experimental test of the proposed OAM RadCom system will also be carried out synchronously. It is expected that a test results of the proposed joint OAM RadCom scheme could be released in our future work.

### APPENDIX

The Fisher information matrix $\mathbf{J}$ with respect to $\vartheta$ can be expressed as

$$
\mathbf{J} = \mathbb{E} \left\{ \begin{bmatrix} \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) \\ \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) \end{bmatrix} \right\}^T
$$

$$
= \mathbb{E} \left\{ \begin{bmatrix} \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) \\ \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) \end{bmatrix} \right\}^T
$$

$$
+ \mathbb{E} \left\{ \begin{bmatrix} \frac{\partial}{\partial \vartheta_1} \ln f(\vartheta) & \frac{\partial}{\partial \vartheta_2} \ln f(\vartheta) \\ \frac{\partial}{\partial \vartheta_2} \ln f(\vartheta) & \frac{\partial}{\partial \vartheta_1} \ln f(\vartheta) \end{bmatrix} \right\}^T
$$

$$
+ \mathbb{E} \left\{ \begin{bmatrix} \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) \\ \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) & \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) \end{bmatrix} \right\}^T
$$

$$
= \mathbf{J}_A + \mathbf{J}_B + \mathbf{J}_C + \mathbf{J}_D, \quad (41)
$$

where $\ln f(\mathbf{E}_R | \vartheta) = \ln f(\mathbf{E}_R | \vartheta) + \ln f(\vartheta)$ is the joint probability density of $(\mathbf{E}_R, \vartheta)$, $\ln f(\mathbf{E}_R | \vartheta)$ is the conditional probability density of $(\mathbf{E}_R | \vartheta)$, and $\ln f(\vartheta)$ is the marginal probability density of $\vartheta$. Due to $\int_{\mathbf{E}_R} f(\mathbf{E}_R | \vartheta) d\mathbf{E}_R = 1$,

$$
\int_{\mathbf{E}_R} f(\mathbf{E}_R | \vartheta) d\mathbf{E}_R = \int_{\vartheta} f(\mathbf{E}_R | \vartheta) d\mathbf{E}_R
$$

Thus, the i-th row and j-th column element $[\mathbf{J}_C]_{ij}$ of $\mathbf{J}_C$ and the j-th row and i-th column element $[\mathbf{J}_D]_{ji}$ of $\mathbf{J}_D$ are derived as

$$
[\mathbf{J}_C]_{ij} = \mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_i} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_j} \ln f(\vartheta)
$$

$$
= \int_{\vartheta} \int_{\mathbf{E}_R} f(\mathbf{E}_R | \vartheta) \frac{\partial}{\partial \vartheta_i} \ln f(\mathbf{E}_R | \vartheta) \frac{\partial}{\partial \vartheta_j} \ln f(\vartheta) d\mathbf{E}_R d\vartheta
$$

$$
= 0,
$$

(43)

that is, $\mathbf{J}_C = 0$ and $\mathbf{J}_D = 0$. After that, the Fisher information matrix $\mathbf{J}$ in (41) is simplified to

$$
\mathbf{J} = \mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta)
$$

$$
+ \mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta)
$$

$$
+ \mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_1} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_2} \ln f(\mathbf{E}_R | \vartheta)
$$

$$
= \mathbf{J}_A + \mathbf{J}_B,
$$

(44)

where $\mathbf{J}_A$ represents the information obtained from OAM echo signals, $\mathbf{J}_B$ represents the priori information.

Considering that $\{n(\ell_k, k_w) = 1, 2, \ldots, U, w = 1, 2, \ldots, W\}$ are independent AWGNs with zero mean and variance $\xi^2$, the conditional probability density $\ln f(\mathbf{E}_R | \vartheta)$ can be written as

$$
\ln f(\mathbf{E}_R | \vartheta) = -UW \ln \sqrt{2\pi \xi} - \frac{1}{2\xi^2} \sum_{u=1}^U \sum_{w=1}^W \left| E_R(\ell_k, k_w) - p(\ell_k, k_w, \vartheta) \right|^2.
$$

(45)

Then, the i-th row and j-th column element $[\mathbf{J}_A]_{ij}$ of $\mathbf{J}_A$ can be expressed as

$$
[\mathbf{J}_A]_{ij} = \mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_i} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_j} \ln f(\mathbf{E}_R | \vartheta)
$$

$$
= -\mathbb{E} \left\{ \frac{\partial}{\partial \vartheta_i} \ln f(\mathbf{E}_R | \vartheta) \right\} \frac{\partial}{\partial \vartheta_j} \ln f(\mathbf{E}_R | \vartheta)
$$

$$
= \mathbb{E} \left\{ \frac{1}{U} \sum_{u=1}^U \sum_{w=1}^W \text{Re} \left[ \frac{\partial^2 p(\ell_k, k_w, \vartheta)}{\partial \vartheta_i \partial \vartheta_j} \right] \right\} - \mathbb{E} \left\{ \frac{1}{U} \sum_{u=1}^U \sum_{w=1}^W \text{Re} \left[ n(\ell_k, k_w) \frac{\partial^2 p(\ell_k, k_w, \vartheta)}{\partial \vartheta_i \partial \vartheta_j} \right] \right\}
$$

$$
= \frac{1}{U} \sum_{u=1}^U \sum_{w=1}^W \text{Re} \left[ \frac{\partial^2 p(\ell_k, k_w, \vartheta)}{\partial \vartheta_i \partial \vartheta_j} \right].
$$

(46)

Supposing that the key state parameters to be estimated in $\mathbf{J}$ satisfy uniform distribution, i.e., $r_m^{\vartheta_0} \sim U(0, r_m)$, $\Theta^{\vartheta_0} \sim U(0, \pi)$, $\varphi^{\vartheta_0} \sim U(0, 2\pi)$ and $\varOmega^{\vartheta_0} \sim U(0, \varOmega_m)$, where $r_m$ and $\varOmega_m$ are the longest distance and maximum rotation velocity that can be detected by the OAM-based target imaging, $q = 1, 2, \ldots, Q$. Then, the marginal probability density $\ln f(\vartheta)$ can be written as

$$
\ln f(\vartheta) = -Q \ln 2\pi^2 r_m \varOmega_m.
$$

(47)
Thus, the $i$-th row and $j$-th column element $[J_B]_{ij}$ of $J_B$ is written as

$$[J_B]_{ij} = E \left\{ \frac{\partial}{\partial \vartheta_j} \ln f(\vartheta) \right\} - E \left\{ \frac{\partial}{\partial \vartheta_i} \ln f(\vartheta) \right\} = 0, \quad (48)$$

i.e., $J_B = 0$. Finally, the Fisher information matrix $J$ is derived as (33).

**ACKNOWLEDGMENT**

The authors would like to thank the editor and the anonymous reviewers for their careful reading and valuable suggestions that helped to improve the quality of this manuscript.

**REFERENCES**

[1] Z. Zhang et al., “6G wireless networks: Vision, requirements, architecture, and key technologies,” IEEE Veh. Technol. Mag., vol. 14, no. 3, pp. 28–41, Sep. 2019.

[2] W. Long, R. Chen, M. Moretti, W. Zhang, and J. Li, “A promising technology for 6G wireless networks: Intelligent reflecting surface,” J. Commun. Inf. Netw., vol. 6, no. 1, pp. 1–16, Mar. 2021.

[3] (Sep. 2018). World Radiocommunications Conference (WRC). [Online]. Available: https://www.itu.int/en/ITU-R/conferences/wrc/Pages/default.aspx.

[4] J. A. Zhang et al., “An overview of signal processing techniques for joint communication and radar sensing,” IEEE J. Sel. Topics Signal Process., vol. 15, no. 6, pp. 1295–1315, Nov. 2021.

[5] L. Zheng, M. Lops, Y. C. Eldar, and X. Wang, “Radar and communication coexistence: An overview: A review of recent methods,” IEEE Signal Process. Mag., vol. 36, no. 5, pp. 85–99, Sep. 2019.

[6] Z. Feng et al., “Joint radar and communication: A survey,” China Commun., vol. 17, no. 1, pp. 1–27, Jan. 2020.

[7] R. M. Mealey, “A method for calculating error probabilities in a radar communication system,” IEEE Trans. Space Electron. Telemetry, vol. 9, no. 2, pp. 37–42, Jun. 1963.

[8] S. Qian, W. Qian, J. Guo, and Y. Zhang, “Radar-communication integration: An overview,” in Proc. 7th IEEE/Int. Conf. Adv. Infocomm Technol., Nov. 2014, pp. 98–103.

[9] C. Sahin, J. Jakabosky, P. M. McCormick, J. G. Metcalf, and S. D. Blunt, “Orbital angular momentum-based two-dimensional super-resolution targets imaging,” in Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP), Nov. 2018, pp. 1–4.

[10] K. Liu, Y. Cheng, X. Li, and Y. Gao, “Microwave-sensing technology using orbital angular momentum: Overview of its advantages,” IEEE Veh. Technol. Mag., vol. 14, no. 2, pp. 711–714, Jun. 2019.

[11] J. Wang, K. Liu, Y. Cheng, and H. Wang, “Three-dimensional target imaging based on vortex stripmap SAR,” IEEE Sensors J., vol. 19, no. 4, pp. 1338–1345, Feb. 2019.

[12] J. Wang, K. Liu, H. Wang, B. Deng, and Z. Zhaung, “Orbital-angular-momentum-based ISAR imaging at terahertz frequencies,” IEEE Sensors J., vol. 18, no. 22, pp. 9230–9235, Nov. 2018.

[13] H. Liu, K. Liu, Y. Cheng, and H. Wang, “Microwave vortex imaging based on dual coupled OAM beams,” IEEE Sensors J., vol. 20, no. 2, pp. 806–815, Jan. 2020.

[14] J. Wang, K. Liu, H. Liu, K. Cao, Y. Cheng, and H. Wang, “3-D object imaging method with electromagnetic vortex,” IEEE Trans. Geosci. Remote Sens., vol. 50, pp. 1–12, 2022.

[15] M. P. Lavery, F. C. Speririts, S. M. Barnett, and M. J. Padgett, “Detection of a spinning object using light’s orbital angular momentum,” Science, vol. 341, no. 6145, pp. 537–540, Sep. 2013.

[16] Z. Zhou, Y. Cheng, K. Liu, H. Wang, and Y. Qin, “Rotational Doppler resolution of spinning target detection based on OAM beams,” IEEE Sensors Lett., vol. 3, no. 5, pp. 1–4, Mar. 2019.

[17] Y. Wang, K. Liu, H. Liu, Y. Qin, and X. Liu, “Detection of rotational object in a quasistatic environment based on orbital angular momentum,” in Proc. Int. Appl. Comput. Electromagn. Soc. Symp. China (ACES), Aug. 2019, pp. 1–2.

[18] Y. Wang, K. Liu, H. Liu, J. Wang, and Y. Cheng, “Detection of rotational object in arbitrary position using vortex electromagnetic waves,” IEEE Sensors J., vol. 21, no. 4, pp. 4989–4994, Feb. 2021.

[19] R. Chen, H. Zhou, M. Moretti, X. Wang, and J. Li, “Orbital angular momentum waves: Generation, detection, and emerging applications,” IEEE Sensors J., vol. 22, no. 2, pp. 840–868, 2nd Quart., 2020.

[20] F. Tamburini, E. Mari, A. Sponselli, B. Thidé, A. Bianchini, and F. Romanato, “Encoding many channels on the same frequency through radio vorticity: First experimental test,” New J. Phys., vol. 14, no. 3, Mar. 2012, Art. no. 033001.

[21] F. E. Mahmoudi and S. D. Walker, “4-Gbps uncompressed video transmission over a 60-GHz orbital angular momentum wireless channel,” IEEE Wireless Commun. Lett., vol. 2, no. 2, pp. 223–226, Apr. 2013.

[22] Y. Yan et al., “High-capacity millimetre-wave communications with orbital angular momentum multiplexing,” Nature Commun., vol. 5, p. 4876, Sep. 2014.

[23] Y. Ren et al., “Line-of-sight millimeter-wave communications using orbital angular momentum multiplexing combined with conventional spatial multiplexing,” IEEE Trans. Wireless Commun., vol. 16, no. 5, pp. 3151–3161, May 2017.

[24] R. Chen, W. Yang, H. Xu, and J. Li, “A 2-D FFT-based transceiver architecture for OAM-OFDM systems with UCA antennas,” IEEE Trans. Veh. Technol., vol. 67, no. 6, pp. 5481–5485, Jun. 2018.

[25] R. Chen, W.-X. Long, X. Wang, and L. Jiandong, “Multi-mode OAM radio waves: Generation, angle of arrival estimation and reception with UCAs,” IEEE Trans. Wireless Commun., vol. 19, no. 10, pp. 6932–6947, Oct. 2020.

[26] W.-X. Long, R. Chen, M. Moretti, J. Xiong, and J. Li, “Joint spatial division and coaxial multiplexing for downlink multi-user OAM wireless backhaul,” IEEE Trans. Broadcast., vol. 67, no. 4, pp. 879–893, Dec. 2021.

[27] W.-X. Long, R. Chen, M. Moretti, and J. Li, “AoA estimation for OAM communication systems with mode-frequency multi-time ESPRIT method,” IEEE Trans. Veh. Technol., vol. 70, no. 5, pp. 5094–5098, May 2021.

[28] Y. Yagi, H. Sasaki, T. Yamada, and D. Lee, “200 Gb/s wireless transmission system using dual-polarized OAM-MIMO multiplexing with uniform circular array on 28 GHz band,” IEEE Antennas Wireless Propag. Lett., vol. 15, no. 6, pp. 1393–1408, Nov. 2016.

[29] R. Chen, Y. Meng, H. Cao, and J. Li, “Orbital-angular-momentum-based electromagnetic vortex imaging,” Int. J. Antennas Propag., vol. 2016, pp. 1–8, May 2016.

[30] G. R. Guo, W. Hu, and X. Du, “Electromagnetic vortex based radar target imaging,” J. Nat. Univ. Defense Technol., vol. 35, no. 6, pp. 71–76, Dec. 2013.

[31] H.-T. Wu, J.-F. Yang, and F.-K. Chen, “Source number estimators using OAM,” Sensors Lett., vol. 3, no. 3, pp. 1–4, Mar. 2009.

[32] Y. Yang, F. Gao, C. Qian, and G. Liao, “Model-aided deep neural network for source number detection,” IEEE Signal Process. Lett., vol. 27, pp. 91–95, 2020.
[41] R. O. Schmidt, “Multiple emitter location and signal parameter estimation,” *IEEE Trans. Antennas Propag.*, vol. AP-34, no. 3, pp. 276–280, Mar. 1986.

[42] H. Gao, L. Xie, S. Wen, and Y. Kuang, “Micro-Doppler signature extraction from ballistic target with micro-motions,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 46, no. 4, pp. 1969–1982, Oct. 2010.

[43] P. Lei, J. Sun, J. Wang, and W. Hong, “Micromotion parameter estimation of free rigid targets based on radar micro-Doppler,” *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 10, pp. 3776–3786, Oct. 2012.

[44] V. C. Chen and S. Qian, “Joint time-frequency transform for radar range-Doppler imaging,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 34, no. 2, pp. 486–499, Apr. 1998.

[45] P. Tichavsky, C. H. Muravchik, and A. Nehorai, “Posterior Cramer-Rao bounds for discrete-time nonlinear filtering,” *IEEE Trans. Signal Process.*, vol. 46, no. 5, pp. 1386–1396, May 1998.

[46] S. Nayak, *Fundamentals of Optimization Techniques With Algorithms*. New York, NY, USA: Academic, 2020.

Wen-Xuan Long (Graduate Student Member, IEEE) received the B.S. degree (Hons.) in rail transit signal and control from Dalian Jiaotong University, Dalian, China, in 2017. She is currently pursuing the double Ph.D. degrees in communications and information systems with Xidian University, China, and the University of Pisa, Italy. Her research interests include broadband wireless communication systems and array signal processing.

Rui Chen (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in communications and information systems from Xidian University, Xi’an, China, in 2005, 2007, and 2011, respectively. From 2014 to 2015, he was a Visiting Scholar at Columbia University, New York. He is currently an Associate Professor and the Ph.D. Supervisor at the School of Telecommunications Engineering, Xidian University. He has published about 80 papers in international journals and conferences and held 40 patents. His research interests include broadband wireless communication systems, array signal processing, and intelligent transportation systems. He is an Associate Editor of *International Journal of Electronics, Communications, and Measurement Engineering* (IGI Global).

Marco Moretti (Member, IEEE) received the degree in electronic engineering from the University of Florence, Florence, Italy, in 1995, and the Ph.D. degree from the Delft University of Technology, Delft, The Netherlands, in 2000. From 2000 to 2003, he was a Senior Researcher with Marconi Mobile. He is currently an Associate Professor with the University of Pisa, Pisa, Italy. His research interests include resource allocation for multicarrier systems, synchronization, and channel estimation. He is currently an Associate Editor of the IEEE TRANSACTIONS ON SIGNAL PROCESSING.

Wei Zhang (Fellow, IEEE) received the Ph.D. degree in electronic engineering from the Chinese University of Hong Kong in 2005. He is currently a Professor at the School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney, Australia. He has published over 200 papers and holds five U.S. patents. His research interests include space information networks, the IoT, and massive MIMO. He has received the five best paper awards from international conferences, the IEEE Communications Society (ComSoc) TCCN Publication Award, and the ComSoc Asia–Pacific Outstanding Paper Award.

Jiandong Li (Fellow, IEEE) received the B.E., M.S., and Ph.D. degrees in communications engineering from Xidian University, Xi’an, China, in 1982, 1985, and 1991, respectively. He was a Visiting Professor with the Department of Electrical and Computer Engineering, Cornell University, from 2002 to 2003. He has been a Faculty Member at the School of Telecommunications Engineering, Xidian University, since 1985, where he is currently a Professor and the Vice Director of the Academic Committee, State Key Laboratory of Integrated Service Networks. His major research interests include wireless communication theory, cognitive radio, and signal processing. He was recognized as a Distinguished Young Researcher by NSFC and a Changjiang Scholar by the Ministry of Education, China, respectively. He served as the General Vice Chair for ChinaCom 2009 and the TPC Chair for the IEEE ICC 2013.