Trajectory Planning of Cellular-Connected UAV for Communication-Assisted Radar Sensing

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Abstract—Being a key technology for beyond fifth-generation wireless systems, joint communication and radar sensing (JCAS) utilizes the reflections of communication signals to detect foreign objects and deliver situational awareness. A cellular-connected unmanned aerial vehicle (UAV) is uniquely suited to form a mobile bistatic synthetic aperture radar (SAR) with its serving base station (BS) to sense over large areas with superb sensing resolutions at no additional requirement of spectrum. This paper designs this novel BS-UAV bistatic SAR platform, and optimizes the flight path of the UAV to minimize its propulsion energy and guarantee the required sensing resolutions on a series of interesting landmarks. A new trajectory planning algorithm is developed to convexify the propulsion energy and resolution requirements by using successive convex approximation and block coordinate descent. Effective trajectories are obtained with a polynomial complexity. Extensive simulations reveal that the proposed trajectory planning algorithm outperforms significantly its alternative that minimizes the flight distance of cellular-aided sensing missions in terms of energy efficiency and effective consumption fluctuation. The energy saving offered by the proposed algorithm can be as significant as 55%.

Index Terms—Joint communication and radar sensing, bistatic synthetic aperture radar, cellular-connected unmanned aerial vehicle, block coordinate descent.

I. INTRODUCTION

RECENT advancements in the fifth-generation and beyond (5G/B5G) networks are increasingly enabling extensive background situation- and position-aware smart applications, including autonomous driving, distant medical care, and smart industry [1]. 5G/B5G networks are also envisioned to offer high-resolution sensing in support of these applications [2]. For this reason, joint communication and radar sensing (JCAS) has been deemed as one of the essential technologies in 5G/B5G systems [3]. By integrating radio communication and sensing into a single system, JCAS measures the reflections of communication signals to sense the location, velocity, and feature signal of targets and motions [4], [5]. This is different from the widely accessible Global Positioning System (GPS), which enables every GPS receiver to locate itself by correlating the preambles/pilots from multiple (four or more) satellites [6], [7]. Neither of the GPS satellites and ground receivers sense the environment or deliver situational awareness, as opposed to JCAS [3].

Cellular-connected unmanned aerial vehicles (UAVs) have been increasingly considered for their operability and applicability to UAV operations over wide areas [8], [9]. Apart from being an aerial user of communication services, a cellular-connected UAV can potentially utilize the cellular signals from corresponding base stations (BSs), and collect the echo signals from the ground (e.g., metallic) objects to perform radar sensing in areas covered by the BSs. Given the excellent mobility, the UAV can potentially form a bistatic synthetic aperture radar (SAR) with its serving BS to sense the environment. While dedicated sensing or radar techniques may detect objects with even better resolution (e.g., because of their wider signal bandwidth and higher signal power), they inevitably bring radio radiation and pollution [3]. Nevertheless, the UAVs are passive receivers, and neither increase the radio footprint of the system nor produce radio pollution.

Fig. 1 illustrates the new cellular-assisted radar sensing by a cellular-connected UAV, referred to as BS-UAV bistatic SAR sensing, where the reflections of the downlink cellular signals are picked up by the UAV and used to produce radio/radar images for object detection. Since the UAV is typically power-constrained, it is critical to carefully plan its trajectory to deliver energy-efficient radar sensing missions and extend mission time. Existing works have only designed the trajectory to minimize the UAV propulsion energy for wireless communication services, such as [10]–[13]. None has considered the energy consumption in the new scenario of cellular-assisted radar sensing with a cellular-connected UAV.

A. Related Work

Existing studies of JCAS systems have typically focused on the beamforming design at the BSs, and have not considered the use of a UAV. These JCAS systems are in
essence monostatic radars, which integrate the transmitter and receiver on the same platform. In [14], waveform design was optimized to confirm the produced signal to the expected sensing waveform subject to the signal-to-interference-and-noise ratio (SINR) requirement for multiuser multiple-input multiple-output (MIMO) communications. In [15], globally optimal waveforms were devised for several expected sensing beam patterns to minimize multiuser interference. In [16], a multibeam technique was introduced for millimeter-wave (mmWave) JCAS with analog antenna arrays, and a fixed transmission subbeam was produced together with direction-changing scanning subbeams across various packets. In [17], a multi-metric waveform was designed for multiple-input single-output (MISO) communications to maximize the SINR at the users. On the other hand, a higher signal power is typically on demand for high-resolution sensing over long ranges, whereas the BSs usually have a limited transmit power. The sensing performance may considerably degrade if the targets are far away from the BS, because of the significant round-trip path loss attenuation of the echoed signals.

UAVs have been emerging as a new type of passive receiver in bistatic radar systems. Unlike a monostatic radar, a bistatic radar uses geographically separated antennas for signal transmission and reception. The German TanDEM-X project (initiated in June 2010) developed the first prototype of a space-borne bistatic radar, relying on twin low-Earth-orbiting (LEO) satellites traveling in near formation [18]. The High-Resolution Wide-Swath (HRWS) project was proposed to be the next-generation German space-borne radar platform for geological and geographical observation beyond 2030, by leveraging the formation movement of an active satellite and three passive satellites [19]. Mounted on mobile platforms, a bistatic SAR can perform HRWS sensing by making use of the relative movements between the SAR and the targets. The small-sized real antenna aperture can realize the capability of a larger aperture radar through data focusing and signal processing [20]. A clutter suppression and mobile target imaging strategy was developed in [21] for a GEO-LEO bistatic SAR system, which was robust against the quickly traveling object with the Doppler centroid ambiguity.

With a geosynchronous (GEO) SAR satellite as the transmitter, a UAV can receive the echo signals from terrestrial targets and achieve two-dimensional (2D) imaging. The flight path of the UAV receiver was planned in [22] for such a GEO-LEO bistatic SAR system to sense rough terrains. A range model was developed in [23] to address the distinctiveness of the GEO-UA V bistatic SAR echo and the variations of the orbit positions of the GEO transmitter. A motion compensation algorithm was proposed in [24] for a mini-UA V-based bistatic SAR system to address the perturbation and spatial variance of the platform. However, none of the existing works [14]–[24] have considered the BS-UA V bistatic SAR, as considered in this paper. None of the existing studies have considered the energy consumption of a UA V-based bistatic SAR system. The works in [22]–[24] were focused on data focusing or image processing algorithms, where the geosynchronous satellites transmitted dedicated signals for ground object detection and did not transmit any data. The energy consumption of the UAV was not considered in [22] for trajectory planning, and the UAV trajectory design was not addressed in [23] and [24]. The results of [22]–[24] cannot apply directly to a BS-UA V bistatic SAR system for energy-efficient trajectory design.

B. Contribution and Organization

In this paper, we propose a novel framework for cellular-aided radar sensing with a cellular-connected UAV,
i.e., BS-UAV bistatic SAR sensing, where the wireless transmissions of a BS serve as the excitation signals of a bistatic SAR system, and the UAV collects the echoed signals for radar sensing. Given a series of landmarks to be sensed/observed, the UAV’s trajectory is optimized to minimize its propulsion energy while satisfying the range and azimuth resolutions of sensing, thereby delivering energy-efficient BS-UAV bistatic SAR sensing missions and extending mission durations. This trajectory planning problem is non-convex because of the non-convexity of its objective function and constraints. We convexify the problem and obtain a quality solution efficiently by utilizing successive convex approximation (SCA) and block coordinate descent (BCD).

The key contributions of the paper are listed as follows.

- A novel BS-UAV bistatic SAR platform is proposed to reuse cellular downlink signals as excitation signals. A cellular-connected UAV receives the reflected signals and conducts radar sensing on landmarks.
- The range and azimuth resolutions of the BS-UAV bistatic SAR are analyzed. An effective sensing area of the BS-UAV bistatic SAR is established to effectively capture a landmark.
- The UAV’s trajectory is optimized to minimize its propulsion energy and ensure that all landmarks are captured in the effective sensing areas with the required range and azimuth sensing resolutions. By applying the SCA and BCD methods, a new algorithm is developed to deliver energy-efficient trajectories with a polynomial complexity.

Extensive simulations corroborate that, in terms of energy efficiency and energy usage fluctuations, the proposed trajectory planning algorithm outperforms a baseline scheme that minimizes the flight distance of the UAV on the cellular-aided radar sensing mission. The proposed algorithm can save up to 55% of the UAV’s propulsion energy, as compared to the baseline scheme.

The remainder of this paper is arranged as follows. Section II describes the system model. Section III formulates the UAV trajectory design problem for the BS-UAV bistatic SAR, and elaborates on the proposed trajectory planning algorithm. Performance evaluations are conducted in Section IV, followed by concluding remarks in Section V.

II. SYSTEM MODEL

In the considered system, a BS is deployed to deliver downlink wireless services to cellular users. A cellular-connected UAV equipped with a side-looking SAR (receiver) flies and collects the echoes (or reflections) of the communication signals originated from the BS, to sense (metallic) objects and gain situational awareness; see Fig. 1. The signals are buffered at the UAV, and offloaded and post-processed (at the BS) after the sensing mission. Given the knowledge of the communication signals, the direct path from the BS to the UAV can be canceled. The remaining echo signals can be used to sense and decide the number and locations of the objects. In this way, the UAV can perform the sensing task by utilizing the communication signals, without the need of dedicated sensing signals, and thereby reduces the radio fingerprint and carbon emission.

The proposed UAV-based sensing platform is insusceptible to inter-cell interference, since it does not need to detect or decode data signals. The transmissions from other BSs can serve as additional illuminating sources to enhance the reflection on the objects. The UAV may utilize the pilot signals of the BSs to extract the reflections of objects [25]. With the knowledge of the pilot signals, the collected reflection signals by the UAV can be correlated to cancel the direct paths from any BSs and extract the reflections by the objects to detect the objects. Alternatively, the UAV may store the captured signals, and only start to process the signals after it returns from the mission and has access to the transmitted signals of the BSs. Then, correlation can be conducted between the captured signals and the transmitted signals to extract the reflections and detect the objects. On the other hand, the proposed trajectory planning algorithm can be performed at the UAV with limited assistance of the BSs. It only requires the information of the landmarks prior to the trajectory planning. The inter-cell interference has little impact on the algorithm, when the algorithm is in operation.

A. Object Distribution

Consider a 2D ground region $A$ with radius $R$. We assume that $A$ is inside the coverage area of the BS. The number of illuminating (e.g., metallic) objects in $A$, denoted by $N(A)$, follows the homogeneous spatial Poisson point process (SPPP). The reason is that the points are uniformly distributed in the circular area (with the same density $\lambda$). The probability density function (PDF) is given by [26]

$$
Pr(N(A) = n) = \frac{\lambda|A|^n}{n!} e^{-\lambda|A|}, \quad n = 0, 1, \ldots,
$$

(1)

where $\lambda > 0$ is the intensity, and $|A|$ is the Lebesgue measure for the size of the region. The objects are uniformly randomly distributed in $A$.

Let $d_i$, $i = 1, \ldots, N(A) - 1$, collect the Euclidean distances from an arbitrarily selected (and designated) object to the other $(N(A) - 1)$ objects within the disk region with radius $R$; and assume that $d_i$, $i = 1, \ldots, N(A) - 1$, are independent and identically distributed (i.i.d.), non-negative random variables. Given the uniform stationary distribution of the objects in the disk region with radius $R$, the cumulative density function (CDF) of $d_i$, $i = 1, \ldots, N(A) - 1$ is given by [27]$^1$

$$
F_{d_i}(l) = 1 + \frac{2}{\pi} \left( \frac{l^2}{R^2} - 1 \right) \cos^{-1} \left( \frac{l}{2R} \right) - \frac{1}{\pi} R \left( 1 + \frac{l^2}{2R^2} \right)^{1/2} \sqrt{1 - \left( \frac{l}{2R} \right)^2}, \quad 0 \leq l \leq 2R.
$$

(2)

$^1$Given the uniform stationary distribution of the objects in the disk region with radius $R$, the PDF of $d_i$, $i = 1, \ldots, N(A) - 1$ is given by [27]

$$
f_{d_i}(l) = \frac{2l}{R^2} \left( \frac{2}{\pi} \cos^{-1} \left( \frac{l}{2R} \right) - \frac{l}{\pi R} \sqrt{1 - \left( \frac{l}{2R} \right)^2} \right), \quad 0 \leq l \leq 2R.
$$
Let $d_{\text{min}}$ denote the shortest of the distance between two objects, i.e., $d_{\text{min}} = \min_{i=1,\ldots,N-1} \{d_i\}$. By exploiting Order Statistics, the CDF of $d_{\text{min}}$ can be given by

$$F_{d_{\text{min}}}(l) = 1 - \left[ 1 - F_{d_i}(l) \right]^{N(A)-1} = 1 - \frac{1}{\pi R} \left( 1 + \frac{l^2}{2R^2} \right) \sqrt{1 - \frac{l^2}{4R^2}} - \frac{2}{\pi} \left( \frac{l^2}{R^2} - 1 \right) \cos^{-1} \left( \frac{l}{2R} \right) \right]^{N(A)-1} . \quad (3)$$

The resolution of the proposed UAV-based bistatic SAR platform is set to be finer than the expected shortest distance between two neighboring objects, i.e., $d_{\text{min}}$, to reasonably distinguish any two different objects. For this reason, we derive the expectation of $d_{\text{min}}$ based on the CDF in (3). The expectation is an integral over $l$, the distance between any two objects in the circular coverage area of the BS with the radius of $R$. Here, $0 \leq l \leq 2R$. Then, the expectation of $d_{\text{min}}$ can be given by

$$\mathbb{E}[d_{\text{min}}] = \int_0^{2R} l \, dF_{d_{\text{min}}}(l) = -l \left[ -F_{d_i}(l) \right]^{N(A)-1} \bigg|_0^{2R} + \int_0^{2R} \left[ 1 - F_{d_i}(l) \right]^{N(A)-1} dl = \int_0^{2R} \left[ \frac{1}{\pi R} \left( 1 + \frac{l^2}{2R^2} \right) \sqrt{1 - \frac{l^2}{4R^2}} - \frac{2}{\pi} \left( \frac{l^2}{R^2} - 1 \right) \cos^{-1} \left( \frac{l}{2R} \right) \right]^{N(A)-1} dl . \quad (4)$$

where $F_{d_i}(0) = 1 - \frac{1}{\pi R}$ and $F_{d_i}(2R) = 1$.

### B. UAV Mobility

In practice, the receiver of a bistatic SAR system flies at a constant altitude, as a stable flight can stabilize the accuracy of the SAR [28]. For this reason, we consider a horizontally flying UAV at a constant altitude, $H$ (in meters), in line with practical implementations, and focus this paper on 2D trajectory planning. Nevertheless, the algorithm developed in this paper can be potentially extended to three-dimensional (3D) trajectory planning with varying UAV altitudes $H_t$, $\forall t$, as will be discussed in Section III.

The UAV executes the sensing mission for a fixed time horizon of $T$ seconds, which is divided into $T_w$ time slots indexed by $t$, and $t = 1, \ldots, T_w$. The duration of a time slot $t$ is $\delta$ seconds. The UAV’s time-varying 2D coordinates are $\mathbf{q}_t = [x_t, y_t]^T$, $\forall t$, with the initial location $\mathbf{q}_0 = [x_0, y_0]^T$. Let $V_t$ denote the UAV speed at time slot $t$, which is upper bounded by $V_m$. The UAV’s mobility constraint is given by

$$\|\mathbf{q}_t - \mathbf{q}_{t-1}\| = \delta V_t \leq \delta V_m, \quad \forall t. \quad (5)$$

For a rotary-wing UAV at a speed $V_t$, the propulsion power at time slot $t$, denoted by $P_t$, is shown by [10]

$$P_t = P_0 \left( 1 + \frac{3V_t^2}{U_{\text{tip}}^2} \right) + P_1 \left( \sqrt{1 + \frac{V_t^4}{4v_0^4} + \frac{V_t^2}{2v_0^2}} \right)^{\frac{1}{2}} + \frac{1}{2} d_f \rho A V_t^3 , \quad (6)$$

where $P_0$ and $P_1$ stand for the fixed blade and induced powers when the aircraft hovers, respectively; $U_{\text{tip}}$ denotes the rotor velocity; $v_0$ is the mean rotor velocity when the aircraft hovers; $d_f$ and $s$ stand for the fuselage drag fraction and rotor solidity, respectively; and $\rho$ and $A$ are the gaseous density and rotor disc area, respectively.

### C. Airborne Bistatic Side-Looking SAR

As shown in Fig. 1, the effective sampling SAR sensing area of the UAV, denoted by $U_t$, is an ellipsoid centered at point $C$ as per slot $t$. We assume that the effective sensing area $U_t$ is always to the right of the UAV, by considering a side-looking SAR [29]. The major axis of the ellipsoid $U_t$, $L_{\text{AB}}$, is perpendicular to the UAV’s heading. Let $\alpha_t \in [0, 2\pi)$ denote the angle between the UAV’s heading and the $x$-axis at time slot $t$. We have

$$\sin \alpha_t = \frac{y_t - y_{t-1}}{\delta V_t}; \quad \cos \alpha_t = \frac{x_t - x_{t-1}}{\delta V_t} . \quad (7)$$

Further let $\eta_t \in (0, \pi/2)$ denote the observation angle of the side-looking SAR at the UAV, which is fixed over time. Given the horizontal coordinates of the UAV, i.e., $U = (x_t, y_t)$ at slot $t$, and $L_{\text{OC}} = H \tan \eta$, the coordinates of the center $C$, i.e., $\mathbf{q}_c = [x_c^T, y_c^T]^T$, can be written as

$$x_c = x_t + H \tan \eta \sin \alpha_t; \quad y_c = y_t - H \tan \eta \cos \alpha_t . \quad (8)$$

To guarantee the sensing performance, $C$ should always be inside the target area $A$. We have $L_{\text{OC}} \leq R, \forall t$.

At any time slot $t$, the range resolution $\delta_r$ and the azimuth resolution $\delta_\delta$ of the BS-UAV bistatic SAR are given by [29, Eq. (5)], [30, Eqs. (24) & (29)]

$$\delta_r = \frac{c}{B (\sin \delta + \sin \theta_t)} ; \quad (9a)$$

$$\delta_\delta = \frac{\lambda_c H}{T_d V_t \cos \eta} . \quad (9b)$$

where $c$ is the speed of light, $\lambda_c$ is the wavelength, $B$ is the transmit signal bandwidth of the BS, $\theta_t \in (0, \pi/2)$ is the incidence angle of the transmitted signal (from the BS) with respect to the point $C$, and $T_d$ is the coherent SAR integration time [31]. Given the horizontal coordinates of the BS $\mathbf{q}_b = [x_b, y_b]^T$ and its height $H_b$, we have

$$\sin \theta_t = \frac{\|\mathbf{q}_c - \mathbf{q}_b\|}{\sqrt{\|\mathbf{q}_c - \mathbf{q}_b\|^2 + H_b^2}} . \quad (10)$$

In order to distinguish the objects, the resolution of the SAR has to be finer than the shortest expected distance between any two objects, $d_{\text{min}}$, i.e., $\delta_r \leq d_{\text{min}}$ and $\delta_\delta \leq d_{\text{min}}$. This resolution requirement is used to detect and differentiate
different objects by leveraging the typically narrow signal bandwidths of cellular systems and, in turn, the poor resolution of sensing [32]. It is worth mentioning that we do not consider object identification in this paper, as it would require wider signal bandwidths to achieve better resolutions for detecting the shape of an object or even imaging the object [30]. Nevertheless, the proposed trajectory planning algorithm would still be relevant under a wider signal bandwidth and correspondingly a finer resolution requirement. The algorithm is generic and suitable for different resolution requirements.

Considering the characteristics of the side-looking SAR, the cosine of the UAV elevation angle is

$$\cos \eta \approx \frac{L_{AE}}{W_g} \approx \frac{\theta_a R_m}{W_g} \approx \frac{\lambda_c R_m}{W_g W_\eta},$$  \hspace{1cm} (11)

where $R_m$ is the slant range (distance) from the SAR antenna to the center of $U_t$ (i.e., point $C$); $W_a$ is the height of the SAR antenna, and $W_g$ is the SAR range extent, i.e., the width of the ground swath covered by the SAR beam, to the right of the UAV; and the vertical beamwidth of the SAR is $\theta_v = \lambda_c/W_a$. The azimuth angular spread is $\theta_a = \lambda_c/L_a$, with $L_a$ being the antenna length parallel to the direction of the UAV’s heading. This spread is due to the interference of the waves emitted from and received by the dipoles of the antenna [33].

The effective sensing area is ellipsoidal, denoted by $U_t$. The ellipsoidal effective sensing area is significantly smaller than the coverage area of the BS, $A$, and is used to sample different parts of the coverage area for object detection. The major and minor axes of the ellipsoidal sensing area, $U_t$, are $R_m = \frac{\lambda_c}{W_a \cos^2 \eta}$ and $\theta_a = \lambda_c/L_a$, respectively. We can obtain from Fig. 2 that $R_m = H/\cos \eta$. Therefore, at any moment, the size of the effective sensing area $U_t$, i.e., $S$, is

$$S = \frac{\pi}{4} \times \frac{\lambda_c}{L_a} \times \frac{\lambda_c H}{W_a \cos^2 \eta}. \hspace{1cm} (12)$$

Given the range and azimuth resolutions of the SAR, and the center and size of the effective sensing area, the BS-UAV bistatic SAR can efficiently sense, detect, and distinguish ground objects in the disk region while the UAV is flying. The details are provided in Section III.

III. PROPOSED FRAMEWORK FOR UAV-ASSISTED JOINT COMMUNICATION AND RADAR SENSING

The UAV performs sensing at a series of landmarks at specified time. The BS-UAV bistatic SAR satisfies the resolution requirements to distinguish objects. The 2D coordinates of the landmark to be sensed at the $t$-th time slot are $q_t = [x_t, y_t]^T$, $\forall t$. We have $G \in U_t$, $\forall t$.

Through antenna configuration, the ellipsoidal shape of $U_t$ can be approximated by a circular area, i.e., $\theta_a = W_g$. The landmark of interest is inside the sensing area $U_t$. Therefore, the distance between the landmark $G$ and the center of the sensing area $U_t$, i.e., point $C$, must not exceed the radius of $U_t$ at any time slot $t$. With the coordinates of the center $C$ and the diameter of $U_t$, i.e., $L_a/L_a$, we have

$$||q_t - q_c|| \leq \frac{\lambda_c}{2L_a}, \forall t. \hspace{1cm} (13)$$

The UAV flies at a constant altitude $H$, and detects objects. The UAV minimizes the overall propulsion energy consumption during the considered time horizon, while maintaining acceptable sensing resolution by using cellular communication signals. This can be formulated as

$$\min_{\{q_t, v_t, \forall t\}} \sum_{t=1}^{T_w} P_t \delta \hspace{1cm} (14a)$$

subject to

$$\frac{c}{B(\sin \eta \sin \theta_t)} \leq d_{\text{min}}, \forall t, \hspace{1cm} (14b)$$

$$\frac{\lambda_c H}{T_d v_t \cos \eta} \leq d_{\text{min}}, \forall t, \hspace{1cm} (14c)$$

$$||q_t - q_{t-1}|| \leq \delta V_t, \forall t, \hspace{1cm} (14d)$$

$$0 \leq V_t \leq V_{\text{max}}, \forall t, \hspace{1cm} (14e)$$

$$||q_t - q_c|| \leq \frac{\lambda_c}{2L_a}, \forall t, \hspace{1cm} (14f)$$

where constraints (14b) and (14c) are the range and azimuth resolution requirements, respectively; (14d) and (14e) are the constraints on the UAV’s mobility and maximum speed, respectively; and (14f) guarantees that the landmarks of interest are always captured at given time slots.

Problem (14) is non-convex because of the non-convexity of the objective (14a) and constraints (14b) and (14f). In what follows, we employ the SCA and BCD techniques to convexify (14), and attain a quality trajectory.

A. SCA-Based Convexification

The convexification starts with the non-convex term of $P_t$ in the objective (14a), i.e., $\left(1 + \frac{V_t^4}{V_0^4} - \frac{V_t^2}{V_0^2}\right)^{q_t^2}$ in (6), by introducing new auxiliary variables $\left\{q_t \geq 0, \forall t = 1, \ldots, T_w\right\}$:

$$q_t^2 = \sqrt{1 + \frac{V_t^4}{4V_0^4} - \frac{V_t^2}{2V_0^2}}, \forall t, \hspace{1cm} (15)$$

which can be reorganized as

$$\frac{1}{q_t^2} = q_t^2 + \frac{V_t^2}{V_0^2}, \forall t. \hspace{1cm} (16)$$

Fig. 2. The $(x, z)$-plane view of the side-looking BS-UAV bistatic SAR effective sensing area, where the UAV heading is perpendicular to the paper, and $W_g$ is the SAR range extent.
Herein, the second component on the right-hand side (RHS) of (6) can be replaced by a linear element $P_1 q_t$, with a newly added constraint (16). As such, $P_t$ is transformed into

$$\tilde{P}_t := P_0 + \frac{3P_1}{U_{t_0}^2} V_t^2 + P_1 q_t + \frac{d_f}{2} \rho s A V_t^3, \forall t.$$  \hspace{1cm} (17)

Here, $\tilde{P}_t$ is jointly convex in $(V_t, q_t)$. With a fixed $\delta$, problem (14) becomes

$$\min_{\{q_t, V_t, q_t, \forall t\}} \sum_{t=1}^{T_w} \tilde{P}_t \tag{18a}$$

s.t. $q_t^2 + \frac{1}{\nu_0} V_t^2 > \frac{1}{\nu_0} q_t^2 + 2q_t (q_t - q_t^{(f)}), \tag{18b}

\begin{align*}
(14b) - (14f).
\end{align*}

Constraint (18b) is attained by slackening the inequality in (16) with inequality. Problems (14) and (18) are equivalent. The reason is that, if (18b) holds with inequality for any $t$, one could always diminish the value of the relevant variable $q_t$ to save the overall power until (18b) takes equality [10].

Problem (18) is still non-convex due to the non-convex constraint (18b), and nevertheless can be resolved with the SCA approach [34] through determining the global lower limit of (18b) at a specified local point. Specifically, the left-hand side (LHS) of (18b) exhibits convexity in $q_t$, and the RHS exhibits convexity in $\{q_t, V_t\}$. Because the first-order Taylor expansion acts as a global lower limit of a convex function [35], we can attain the lower limit for the RHS of (18b), as given by:

$$q_t^2 + \frac{1}{\nu_0} V_t^2 \geq q_t^{(f)} + \frac{1}{\nu_0} V_t^{(f)} + 2q_t^{(f)} (q_t - q_t^{(f)}), \tag{19}$$

where $q_t^{(f)}$ and $V_t^{(f)}$ are the respective values of the variables at the $\ell$-th iteration of the SCA method.

We proceed to convexify constraints (14b) and (14f), since the other constraints (14c)-(14e) are all convex by now. This starts by rewriting (14b) as

$$\sin \theta_t \geq \frac{c}{B d_{\min}} - \sin \eta. \tag{20}$$

With $\sin^2 \theta_t = 1 - \cos^2 \theta_t$, we have

$$H_b^2 \left\| q_t^{(f)} - q_t \right\|^2 + H_b^2 \leq 1 - \left( \frac{c}{B d_{\min}} - \sin \eta \right)^2. \tag{21}$$

Introduce slack variables $w_t = \sin \alpha_t$ and $u_t = \cos \alpha_t, \forall t$. From (5) and (7), we have additional constraints on $w_t$ and $u_t$:

$$\begin{align*}
-1 \leq w_t \leq \frac{y_t - y_{t-1}}{\delta V_t}, & \forall t, \tag{22a}\\
\frac{x_t - x_{t-1}}{\delta V_t} \leq u_t \leq 1, & \forall t. \tag{22b}
\end{align*}$$

Constraint (22) is non-convex because of the coupling between $V_t$ and $w_t$ (or $u_t$).

With $w_t$ and $u_t$, (21) can be reorganized as

$$\begin{align*}
(x_t + w_t H \tan \eta - x_{b_t})^2 + (y_t - u_t H \tan \eta - y_{b_t})^2 & \geq \frac{H_b^2}{1 - \left( \frac{c}{B d_{\min}} - \sin \eta \right)^2} - H_b^2 := C_r, \forall t. \tag{23}
\end{align*}$$

The LHS of (23) is convex in $\{q_t, w_t, u_t\}$. The RHS of (23) is a constant and defined as $C_r$ for illustration convenience, given the predetermined parameters $H_b$, $c$, $B$, $d_{\min}$, and $\eta$. We convexify (23) by determining the first-order Taylor expansion of its LHS at the local point attained during the $\ell$-th iteration of the SCA:

Given $\{w_t^{(f)}, u_t^{(f)}\}$, (23) can be linearized in $q_t$:

$$\begin{align*}
(x_t^{(f)} + w_t^{(f)} H \tan \eta - x_{b_t})^2 + (y_t^{(f)} - u_t^{(f)} H \tan \eta - y_{b_t})^2 & \geq 2(x_t^{(f)} + w_t^{(f)} H \tan \eta - x_{b_t})(x_t - x_{b_t}^{(f)}) \tag{24}
\end{align*}$$

$$+ 2(y_t^{(f)} - u_t^{(f)} H \tan \eta - y_{b_t})(y_t - y_{b_t}^{(f)}) \geq C_r, \forall t. \tag{25}$$

As done to (23), constraint (14f) can be rewritten as

$$\begin{align*}
(x_t + w_t H \tan \eta - x_{b_t})^2 + (y_t - u_t H \tan \eta - y_{b_t})^2 & \leq \left( \frac{\lambda_c}{2L_a} \right)^2, \forall t. \tag{26}
\end{align*}$$

which is convex in $\{q_t, w_t, u_t\}$. As a result, problem (18) is transformed into

$$\min_{\{q_t, V_t, q_t, w_t, u_t, \forall t\}} \sum_{t=1}^{T_w} \tilde{P}_t \tag{27a}$$

s.t. $q_t^2 + \frac{1}{\nu_0} V_t^2 \geq q_t^{(f)} + \frac{1}{\nu_0} V_t^{(f)} + 2q_t^{(f)} (q_t - q_t^{(f)}) + 2q_t^{(f)} V_t^{(f)} (V_t - V_t^{(f)}), \forall t, \tag{27b}$

where (27b) tightens the original constraint (18b) by using a lower bound of its RHS. Since problem (27) is a tightened version of problem (18), the feasible region of (27) is also the feasible region of (18); not the other way around.

### B. Block Coordinate Descent (BCD)

Problem (27) is still non-convex due to the non-convexity of constraint (22). We apply the BCD to optimize $\{q_t, V_t, q_t\}$ and $\{w_t, u_t\}$ in an alternating manner, because the variables $V_t$ and $\{w_t, u_t\}$ are coupled in the non-convex constraint (22): Given fixed $\{w_t, u_t\}$, problem (27) is reduced to the following convex problem:

$$\min_{\{q_t, V_t, q_t, \forall t\}} \sum_{t=1}^{T_w} \tilde{P}_t \tag{28a}$$
the interior point method with the complexity of $O(N^3.5)$ per iteration. The overall computational complexity of Algorithm 1 is $O(N^3.5)$ per iteration. Interested readers can refer to [35] for a detailed introduction of the interior point method and convex optimization in general.

Let $x$ and $x^*$ denote a feasible solution and the optimal solution to problem (27), respectively. Also, let $P$ denote the objective value of problem (27). As established in [37], given the convergence precision $\epsilon$ of the algorithm, i.e., $|P(x) - P(x^*)| \leq \epsilon$, the interior-point method takes $O(\log \frac{1}{\epsilon})$ iterations before convergence. Therefore, Algorithm 1 has a polynomial complexity of $O(N^3.5 \log \frac{1}{\epsilon})$.

IV. SIMULATION RESULTS

This section provides the simulation results of the proposed trajectory planning algorithm for BS-UAV bistatic SAR using MATLAB. The entire sensing period lasts $T = 300$ s with each time slot of $\delta = 0.5$ s, unless stated otherwise. The default setting of the landmarks (and associated sensing time) is a series of points with the first 15 of them, i.e., when $t \leq 150$ s, along the $y$-axis starting from (0, 0), and the rest along the $x$-axis starting from $q_{16}^T$. The adjacent landmarks are apart for an equal distance. The UAV initial location is $q_0 = [-1000, -500]^T$ m. The BS is located at $q_b = [1000, -1000]^T$ m, with the height $H_b = 50$ m. The other parameters concerning the BS-UAV bistatic SAR sensing performance and the UAV propulsion power are provided in Table I.

We note that the standard sub-6 GHz band has been extensively deployed to provide broad 5G coverage, where the antennas are typically horizontally or quasi-horizontally oriented in the sub-6 GHz band [32]. The transmission bandwidth is typically narrow in the sub-6 GHz band, e.g., up to 100 MHz, and consequently the range resolution could be poor [38]. Nevertheless, a bandwidth of 150 MHz can be
achieved in a standard sub-6 GHz band by using carrier aggregation techniques [39]. For instance, China Mobile deployed a 4G and 5G concurrent integrated network supporting a transmission bandwidth of up to 160 MHz at the 2.6 GHz band in 2019 [40]. On the other hand, the 5G new radio (NR) has also specified the use of mmWave bands. The propagation of mmWave signals can be limited within a close range of the BS, subject to antenna orientation (i.e., downtilt) [32]. Nevertheless, the signals can still be reflected by objects (e.g., with smooth metallic surfaces) or the edges of objects [41], [42], and captured by the UAV. Given the quasi-optical property of mmWave signals [43], the ground reflections (and reflections by other non-smooth surfaces, e.g., walls, vegetation, etc.) are expected to be substantially weaker, resulting in strong contrast to manifest objects [43].

We also note that no existing studies have addressed the problem of energy-efficient trajectory design for the considered UAV-based bistatic SAR system, as discussed in Section I-A. In other words, no existing algorithm is directly comparable to the proposed algorithm. With due diligence, we come up with a new baseline scheme for the considered problem, which minimizes the total flight distance of the UAV without considering the energy consumption of the UAV, i.e., \( \min_q \sum_i \|q_i\| \). The baseline has a convex objective function, while its constraints can be convexified in the same way as done in Algorithm 1.

Fig. 3(a) shows the expected shortest distance between any two objects in the area, \( d_{\text{min}} \), versus the radius of the given area, \( R \); Fig. 3(b) plots the convergence of the objective value (27a) under the default setting; and Fig. 3(c) plots the UAV propulsion power vs. speed.

This is because the UAV can move faster, and the propulsion power first decreases and then increases at the increasing speed of the UAV, as shown in Fig. 3(c). Fig. 3(c) plots the UAV power consumption \( P_t \) in (6) by varying the instantaneous speed of a rotary-wing UAV from 0 m/s to 70 m/s. The UAV’s propulsion power is independent of its trajectory and heading. The UAV consumes the least power when its speed is about 35 m/s, validating the results in Fig. 3(b).

Fig. 4 shows the per-slot energy consumption of the rotary-wing UAV conducting the BS-UAV bistatic SAR sensing under the proposed and baseline schemes when the landmarks of interest are separated by 30 m and 200 m, under the default setting.

### Table I

| Parameter                        | Value               |
|----------------------------------|---------------------|
| Transmission bandwidth, \( B \)  | 150 MHz             |
| Wavelength, \( \lambda_c \)      | 0.1 m               |
| Coherent integration time, \( T_d \) | 1 s                 |
| SAR observation angle, \( \eta \) | \( \pi/4 \)         |
| Minimum object distance, \( d_{\text{min}} \) | 20 m               |
| UAV weight and altitude, \( H \)  | 2 kg, 1000 m        |
| Maximum UAV speed, \( V_m \)     | 50 m/s              |
| Blade profile and lip speed, \( P_0 \) and \( U_{\text{exp}} \) | 3.4 W, 60 m/s      |
| Rotor induced power and velocity, \( P_t \) and \( v_0 \) | 118 W, 5.4 m/s     |
| Rotor solidity and disc area, \( s \) and \( A \)  | 0.02, 0.5 m²        |
| Air density and fuselage drag fraction, \( \rho \) and \( d_f \) | 1.225 kg/m³, 0.3    |
It is interesting to notice that the baseline scheme is better than the proposed algorithm in terms of per-slot UAV power consumption when $t \leq 50$ s and the spacing between adjacent landmarks is 30 m. This is because the objective of the proposed algorithm, i.e., (14a), is to minimize the total energy consumption. As a result, the algorithm has the UAV fly slowly away from a landmark (while still keeping the landmark within its effective sensing area) at the beginning of the sensing mission to benefit the later stage of the mission. The UAV has to restrain its speed at the beginning of the mission at the cost of high energy consumption, as will be shown in Fig. 5. On the other hand, the baseline schemes, the UAV first catches up with the nearest landmark at its highest speed, and then flies at a relatively stable speed to satisfy the resolution requirements. This can cause drastic changes in the instantaneous power consumption of the UAV under the baseline method, as already shown in Fig. 4.

Fig. 7 plots the UAV trajectory when $T = 600$ s. The landmarks are separated by 30 m and distributed in a staircase (that is, two street blocks situated along a diagonal). The effective sensing area of the BS-UAV bistatic SAR is indicated by the black, magenta, or green circles, when $t = 10$ s, 250 s, 350 s, 450 s, and 590 s, respectively. It is shown in Fig. 7 that the BS-UAV bistatic SAR can always capture the landmarks in its sensing coverage at the required time slots.

Fig. 8 plots the UAV trajectory when the landmarks are separated by 100 m and distributed in a square (e.g., a closed loop around a triangular street block), $T = 600$ s, and $H = 1000$ m (Fig. 8(a)) or 1200 m (Fig. 8(b)). The effective sensing area of the BS-UAV bistatic SAR is shown when $t = 250$ s. We see that the UAV takes a much shorter flight path around the landmarks to satisfy the sensing resolution requirements, which is at the cost of a much higher propulsion energy consumption, as to be shown in Fig. 9.

Fig. 9 plots the per-slot energy consumption of the proposed scheme when the landmarks are distributed in a staircase...
Fig. 8. The UAV trajectory by the proposed scheme, where the landmarks of interest are separated by 100 m and $T = 600$ s.

(i.e., the two diagonally situated street blocks) or a square (i.e., the closed loop of a triangular street block), with the spacing of 30 m and 100 m, respectively. Here, $T = 600$ s, and $H = 1000$ m or 1200 m. We see that the UAV consumes less energy when the landmark spacing or the UAV altitude is larger, as the UAV embraces more flexibility to design an energy-efficient trajectory and meet the sensing requirements. The per-slot energy consumption of the baseline approach is also plotted for the landmarks arranged on the square with the spacing of 100 m, and the UAV elevation is $H = 1200$ m. We see that the proposed scheme consumes dramatically lower energy than the baseline, and prevents drastic fluctuations in the per-slot consumption of the UAV propulsion energy.

Fig. 9. The UAV per-slot energy consumption by the proposed scheme when the landmarks of interest are distributed like a staircase (separated by 30 m, $H = 1000$ m), and a square (separated by 100 m, $H = 1000$ m and 1200 m), and $T = 600$ s.

Fig. 10. The UAV trajectory and per-slot energy consumption by the proposed and baseline schemes when the landmarks of interest are distributed randomly, $H = 1000$ m and $T = 300$ s.

Last but not least, we examine the performance of the proposed BS-UAV bistatic SAR under different transmission bandwidths $B$ in the sub-6 GHz band and the mmWave band. Table II shows the range resolutions of the SAR, where $B$ is 50 MHz, 100 MHz, and 150 MHz at the sub-6 GHz band, and 200 MHz at the mmWave band. Here, $\theta_r$ is assumed to be $\pi/3$. 
We see that the resolutions are always better than the expected shortest distance between any two objects, $d_{\text{min}}$, in other words, the SAR can effectively distinguish ground objects. Fig. 11 shows the UAV trajectory by the proposed and baseline schemes, where the landmarks are separated by 200 m, and the transmission bandwidth $B$ is 50 MHz and 100 MHz. The other settings are consistent with those in Fig. 6. By comparing Fig. 11 to Fig. 6, we see that the UAV trajectory has similar patterns while satisfying the sensing accuracy.

V. Conclusion

This paper proposed a novel framework of cellular-aided radar sensing with a BS-UAV bistatic SAR platform. The trajectory of the UAV was optimized to minimize the propulsion energy while satisfying the range and azimuth resolutions of sensing. The trajectory planning problem was convexified and solved efficiently by utilizing the SCA and BCD methods. Extensive simulations revealed that, in terms of energy efficiency and effective consumption fluctuation, the proposed trajectory planning algorithm is superior to its alternative that minimizes the flight distance of a cellular-aided sensing mission. The energy saving can be as large as 55% for the UAV, by running the proposed algorithm. In the future, we will extend the BS-UAV bistatic SAR system to a fixed-wing UAV-based platform, where a more sophisticated propulsion energy model and dynamic/mobility model will be taken into account.

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