

Wireless Transmitter Localization Using Passive Sensing Enhanced With UAV-Mounted RIS

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ABSTRACT This paper studies the use of Uncrewed Aerial Vehicle (UAV)-borne Reconfigurable Intelligent Surface (RIS) to localize arbitrary transmitters using Time Difference of Arrival (TDoA). Applications include jammer localization and search-and-rescue scenarios, where there is insufficient knowledge of the transmitter characteristics. Our methodology improves on classical TDoA systems by not requiring geographically separated, precisely synchronized receivers or having previous knowledge of the propagation environment. By utilizing the high mobility of the UAV, we position the RIS anywhere and redirect the signal to a centralized receiver, where synchronization is trivial. The added RIS in the signal path incurs extra travel time. By compensating for this additional time during the delay computation, we simplify the problem back to classical TDoA for localization, without the need for separated and synchronized receivers. Extensive simulations show that our system can achieve sub 10-meter-level accuracy for transmitters up to 500 meters away.

INDEX TERMS Reconfigurable intelligent surfaces, autonomous aerial vehicles, localization, passive sensing, time difference of arrival.

I. INTRODUCTION

AS 5G, 6G, WiFi, and other wireless technologies proliferate, the need for enhanced techniques for localizing wireless devices rises. For a wide applicability of these techniques, we assume that these devices are non-cooperative and do not aid in the localization process. We capture the wireless signals passively using an ad-hoc deployable system with a central receiver and multiple Uncrewed Aerial Vehicles (UAVs) equipped with Reconfigurable Intelligent Surface (RIS) and use them to localize non-cooperative wireless devices.

Passive localization of wireless transmitters plays a key role in search-and-rescue and jammer localization scenarios, among others, leading to increased safety and interference-free communications. Time Difference of Arrival (TDoA) techniques are among the most established approaches [1], enabling accurate localization when signals are observed via multiple geographically separated paths [2]. However, conventional TDoA systems require either multiple synchronized receivers or known propagation conditions, both of which are

difficult to guarantee in outdoor and ad-hoc scenarios [3]. When receivers are not synchronized, timing errors quickly lead to high localization error [4], a 1 nanosecond timing error leads to 30 cm of range estimate error.

Recent advances in passive sensing have shown that non-cooperative transmitters can be localized using distributed passive sensors that exploit Line-of-Sight (LoS) and scattered signal components through cross-correlation-based delay measurements [5]. Nevertheless, such approaches remain fundamentally limited by long-distance synchronization and the uncontrollable nature of the natural propagation environment. When the LoS path is blocked, or multipath components are weak or poorly separated, reliable delay estimation becomes challenging.

RISs have emerged as a promising technology to reshape wireless propagation by creating controllable reflection paths. While RIS-assisted localization has been extensively studied, existing solutions rely on cooperative transmitters, pilot signals, or structured waveforms [6]. In parallel, UAVs have been explored as mobile sensing platforms and communication relays, offering flexible deployment and

improved geometric diversity [7]. However, existing UAV-RIS systems assume active sensing or communication-centric operation, and do not address purely passive localization of unknown emitters. The assumption of active sensing simplifies the problem by allowing the transmitter and receiver to communicate and agree on a waveform or other characteristics of the signal. In a purely passive setting, the localization system has to make do with the signal that is already being transmitted.

In our method, we use RIS to harness multipath propagation. By mounting them on UAVs, we can flexibly distribute them over an area. The RISs redirect the signal towards a centralized receiver with multiple receive-chains, eliminating the problem of strict synchronization with geographically distributed receivers [4], as the co-located receiver-chains can easily share the same reference clock. After redirection, we compute the delay from a pair of signal paths and compensate for the extra incurred travel time due to the reflection from the RIS. Using the compensated computed delays, we apply known TDoA methods, where the UAV-mounted RISs act as anchorpoints, i.e., virtual receivers.

This method requires an algorithm for positioning the UAVs in geometrically favorable positions such that they create strong signal paths between transmitter and receiver via the RIS. To create those paths, a beam sweeping algorithm to find the optimal configuration for the RIS is also necessary. Once the signals are captured, Fast Fourier Transform-based methods compute the cross-correlation and thus the delay between the two total paths. The final step before localization is compensating for the extra travel time for the RIS, following simple geometry.

The main contributions of this paper are summarized as follows.

- We introduce a UAV-mounted RIS architecture for passive, non-cooperative wireless transmitter localization, eliminating the need for a cooperative transmitter, tight synchronization with geographically distributed sensors, or fixed ground infrastructure.
- We develop a signal and system model that enables cross-correlation-based TDoA estimation using RIS-induced reflection paths, in contrast to the conventional distributed receiver approach.
- We propose practical algorithms for UAV positioning, RIS beam configuration, compensated TDoA estimation, and localization, overcoming the rigidity of fixed infrastructure and synchronization constraints of existing approaches.
- We provide the first analysis of the proposed approach through simulation and characterize its performance under varying geometric constraints, measurement errors, and positioning uncertainty.

To make the problem tractable and isolate the core contribution, we adopt several modeling assumptions. Throughout this paper, we assume a single, static, ground-based transmitter, transmitting a noise-like, sufficiently wideband signal at a fixed frequency during the localization interval to enable time-delay estimation via cross-correlation. We model the propagation environment as predominantly line-of-sight

between the transmitter and each RIS, with other multipath components assumed to be negligible due to directional reception at the receiver and RIS beamforming. We assume that each RIS generates a single dominant reflection path toward a dedicated receiver chain, and inter-path interference is neglected. Furthermore, we assume ideal RIS behavior with continuous phase control and negligible hardware impairments, as well as perfectly synchronized and phase-coherent receiver channels within the centralized receiver. The UAVs are treated as static during the measurement interval, and their nominal positions are known up to small zero-mean perturbations. These assumptions define a controlled baseline that allows us to evaluate the feasibility and fundamental limits of UAV-assisted passive TDoA localization. Relaxing these assumptions is left for future work.

The rest of the paper is structured as follows. In Section II, we discuss related work. Next, in Section III, we provide an overview of the system components and the used signal model. In Section IV, we explain the localization method and the necessary algorithms. Section V shows our simulation setup and the results. In Section VI, we discuss our findings. Finally, Section VII hosts our conclusions.

II. RELATED WORK

To the best of our knowledge, no prior work has explicitly investigated outdoor passive localization of non-cooperative transmitters using UAV-mounted RIS. Existing works cover individual components of this idea as (cf., Section II-A) passive sensing without RIS assistance, (cf., Section II-B) RIS-enabled localization assuming active cooperation with user devices, or (cf., Section II-C) UAV-mounted RIS for communication enhancement in areas with poor coverage [8].

A. PASSIVE SENSING AND TDOA/AOA-BASED LOCALIZATION

Passive localization relies on receive-only techniques that extract parameters such as TDoA and Angle of Arrival (AoA) from emitted signals, enabling the localization of an arbitrary, non-cooperative transmitter. A recent survey on Non Line-of-Sight (NLoS) localization [9] shows that outdoor passive sensing is fundamentally constrained by weak or unpredictable reflections, the absence of LoS, and degraded TDoA/AoA estimation. Existing NLoS approaches, including geometric inference, fingerprinting, and virtual-station methods, depend on naturally occurring multipath, which rarely provides strong, well-separated reflection paths suitable for precise delay extraction in outdoor environments [10].

Several works study delay-based and angle-based passive localization under realistic propagation conditions. The AoA-differential-time-delay (DTD) framework in [5] exploits both direct and scattered components, while cooperative passive sensing in Integrated Sensing And Communication (ISAC) systems leverages multi-BS fusion to improve delay estimation [11]. Another study investigated a direct localization approach using movement-driven virtual large arrays to enhance AoA-based accuracy [12]. Passive techniques have further been applied to jammer localization [13] and Received Signal Strength (RSS)/AoA-fusion methods.

Overall, no passive-sensing approach provides a mechanism to engineer a strong, geometrically useful reflection path. Existing methods depend entirely on ambient multipath whose geometry and strength cannot be controlled, fundamentally limiting passive localization when LoS is blocked or multipath is weak. Therefore, it motivates the use of UAV-mounted RIS to create intentional, high-quality reflections for reliable outdoor TDoA estimation.

B. RIS-BASED LOCALIZATION TECHNIQUES

Existing RIS-aided localization methods broadly fall into two categories: (i) two-step geometric schemes that estimate parameters such as AoA, AoD, or ToA before position inference, and (ii) fingerprinting or learning-based approaches that map RIS-reflected signal patterns directly to locations [6]. All such methods rely on structured User Equipment (UE) transmissions or pilot signals.

High-dimensional RIS-domain features extracted via deep learning have been shown to improve localization performance [14], exemplifying learning-based approaches, while hybrid Time of Arrival (TOA) and AoA schemes exploit controlled phase configurations to enhance parameter observability [15], representative of geometric methods. Related approaches use active Radio Frequency (RF) relays or RIS to engineer favorable propagation conditions [16], [17], illustrating the benefits of controllable reflections but still requiring transmitter cooperation.

RIS-assisted localization has also been explored in ISAC frameworks, including millimeter-wave scenarios under full blockage [18], as well as schemes that generate multiple resolvable paths via successive RIS configurations to enable trilateration [19]. Robustness under malicious interference has been studied through iterative RIS phase optimization [20], again assuming known pilot signals.

Existing RIS-aided localization approaches fundamentally depend on transmitter cooperation through pilots, structured sensing frames, or controllable waveforms. In contrast, it remains unexplored whether RIS-reflected paths can support reliable cross-correlation-based delay estimation in a fully passive, non-cooperative setting. This motivates our investigation of a UAV-mounted RIS as a controllable reflector for outdoor passive localization.

C. UAV PLATFORMS FOR LOCALIZATION AND SENSING

UAVs have become an important component in wireless sensing and localization due to their high mobility, flexible deployment, and ability to establish strong LoS links. Their elevated vantage point enables improved geometric diversity, enhanced coverage, and rapid reconfigurability compared to ground-based platforms, motivating their use as sensing nodes, cooperative communication relays, or localization targets.

A comprehensive survey on RIS-enabled UAV communications and sensing is provided in [7], highlighting challenges such as high mobility, Doppler effects, and dynamic LoS-dominant channels. The survey further emphasizes the suitability of RIS technologies for UAV-based ISAC architectures, enabling beam control, constructive LoS engineering,

and near-field focusing. However, these works primarily address communication and cooperative sensing scenarios rather than passive localization of unknown emitters.

Recent studies demonstrate how UAVs can act as controllable reflector platforms for localization and sensing. For example, [21] investigates a UAV-mounted RIS for maritime secure sensing, jointly optimizing UAV trajectory and RIS phase profiles to shape received signal geometry. In another work, they jointly used UAV and building-mounted RIS to get more favorable signal conditions [22]. While differing from our passive localization setting, these works highlight the potential of RIS-equipped UAVs to engineer favorable sensing geometries beyond what static infrastructure allows.

Nevertheless, these systems primarily focus on communication enhancement or cooperative sensing scenarios. Consequently, passive localization of unknown transmitters using UAV-mounted RISs remains unexplored.

D. COMPARISON OF EXISTING LOCALIZATION APPROACHES

To better position the proposed approach, we compare it with two representative TDoA-based localization architectures: (i) pre-deployed distributed receiver networks and (ii) UAV-borne receiver systems. Table 1 summarizes the key differences.

In conventional TDoA systems with pre-deployed infrastructure, multiple geographically separated receivers are installed at fixed locations and connected to a central processing unit. These systems require precise synchronization across all receivers, typically achieved via wired connections or high-precision timing protocols. While such setups enable accurate localization, their applicability is limited to predefined coverage areas, making them unsuitable for ad-hoc or rapidly changing scenarios.

To address this limitation, UAV-borne receiver systems have been proposed. In these systems, receivers are mounted on UAVs and deployed dynamically around the area of interest. This improves flexibility and extends the operational range compared to fixed infrastructures. However, the fundamental challenges of distributed TDoA systems remain: the receivers still require tight synchronization, and their measurements must be transmitted to a central unit for joint processing. Achieving reliable wireless synchronization and high-rate data transfer between multiple UAVs introduces significant communication overhead and increases system complexity. Furthermore, the power consumption of onboard receivers and communication modules reduces flight time, imposing practical constraints on UAV size and endurance.

In contrast, the proposed UAV-mounted RIS architecture fundamentally changes the system design by replacing the active airborne receivers with passive reflecting elements. Instead of capturing signals at multiple distributed receiver sites, the RIS-equipped UAVs redirect the transmitted signal toward a localized receiver with multiple synchronized receive-chains. This eliminates the need for long-distance synchronization and site-to-site data transfer, as all signals are acquired at a single location with a shared clock reference.

TABLE 1. Comparison of representative localization approaches.

Aspect	Fixed Receiver Sites [1, 4, 5, 9]	UAV-Borne Receivers [2]	Existing UAV-RIS Localization [7, 21]	Proposed UAV-RIS Assisted Localization
Ad-hoc deployability	×	✓	✓	✓
No fixed infrastructure required	×	✓	✓	✓
UAV-mounted RIS	×	×	✓	✓
Controllable propagation path	×	×	✓	✓
Non-cooperative transmitter localization	✓	✓	×	✓
Centralized receiver architecture	×	×	×	✓
Delay compensation	×	×	×	✓
No raw signal backhaul required	×	×	×	✓

This design offers several advantages. First, synchronization is much simpler at the centralized receiver, avoiding the complexity of wireless clock distribution. Second, since RIS elements are largely passive and do not require signal amplification or baseband processing, the onboard power consumption is significantly reduced compared to UAV-borne receivers. Third, the absence of communication for data aggregation eliminates the need for additional bandwidth and reduces system overhead. At the same time, the mobility of UAVs preserves the flexibility of ad-hoc deployment.

Overall, the proposed approach combines the deployment flexibility of UAV-based systems with the simplicity and robustness of centralized receiver architectures, while mitigating the key limitations of synchronization, communication overhead, and power consumption present in existing TDoA-based localization methods.

E. RESEARCH GAPS AND POSITION OF OUR WORK IN THE LITERATURE

In this study, we exploit the controllable propagation capabilities of RIS together with the mobility of UAV platforms to enable passive localization of non-cooperative wireless transmitters using TDoA-based measurements. Existing approaches suffer from three fundamental limitations.

First, passive localization methods such as AoA-based techniques, multi-sensor AoA-TDoA schemes, ISAC-based sensing, and virtual large arrays depend on naturally occurring multipath, i.e. they do not engineer propagation paths [5], [9], [10], [11], [12], [13]. The geometry and strength of these reflections cannot be controlled. Performance therefore degrades in outdoor environments with blocked LoS or sparse multipath. There is no way to deliberately create a strong, geometrically useful reflection.

Second, RIS-enabled localization can create virtual LoS paths and improve geometric diversity [6], [14], [15], [16], [18], [19], [20]. However, existing approaches assume transmitter cooperation through pilot signals, structured frames, or controlled waveforms. It remains unknown whether RIS-reflected paths, without any transmitter cooperation, can support reliable cross-correlation-based delay estimation.

Third, prior work on UAV-mounted RIS systems shows that mobility and beam control can improve communication, tracking, and sensing performance [7], [21]. However, these methods are cooperative and rely on radar pulses or communication signals. No study has examined purely passive, receive-only localization of an unknown emitter using a UAV-mounted RIS. The geometric and Signal-to-Noise Ratio (SNR) conditions under which a controllable RIS-induced reflection enables robust TDoA estimation under LoS blockage also remain undefined.

Motivated by these gaps, our work addresses the following research questions:

- What sources of error have an impact when localizing a transmitter using UAV-mounted RIS in a purely passive, non-cooperative setting?
- What is the minimum SNR required for reliable cross-correlation-based delay estimation via a single RIS-reflected path?
- What localization accuracy is achievable under realistic outdoor propagation conditions?

III. SYSTEM MODEL

Throughout this paper, we use the following mathematical notation. Lowercase letters such as τ_i denote scalar values. Bold lowercase letters, $\mathbf{a}$, denote position vectors in Euclidean space. Bold uppercase letters denote matrices: $\mathbf{B}$. Calligraphic uppercase letters denote sets: $\mathcal{C}$. $\hat{\mathbf{a}}$ denotes an estimate of $\mathbf{a}$. The operator $\|\cdot\|$ denotes the Euclidean norm, such that $\|\mathbf{a}\|$ represents the distance of $\mathbf{a}$ from the origin. The operator $\text{diag}(\cdot)$ constructs a diagonal matrix from its arguments. The notation $\mathcal{CN}(0, \sigma^2)$ denotes a complex Gaussian distribution with zero mean and variance σ^2 . The superscript $(\cdot)^*$ denotes complex conjugation. The speed of light in vacuum is denoted by $c \approx 3 \times 10^8$ m/s. We refer to continuous-time delay in seconds as τ , propagation distance in meters as $d = c\tau$, and delay in samples as $n = \tau f_s$. In addition, we use the term ‘reflector’ to denote the combined UAV+RIS unit.

A. GEOMETRIC MODEL

We consider a UAV-assisted RIS-based passive localization setup in a 3D Euclidean space. The detailed geometric overview is illustrated in Figure 1. A single-antenna transmit-

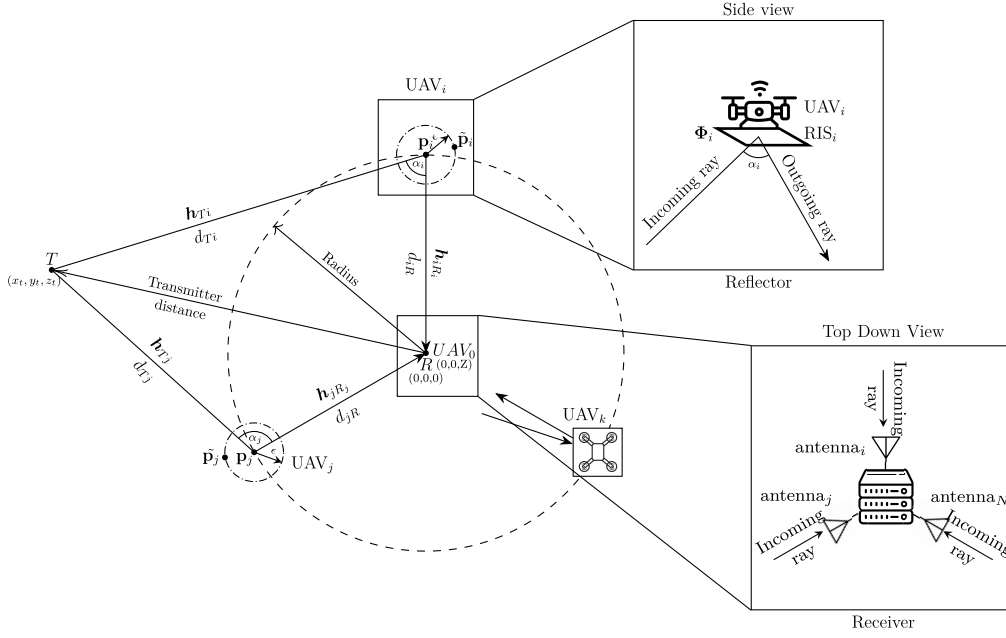


FIGURE 1. Illustration of the UAV-borne RIS-assisted wireless transmitter localization system, where $UAV_i, UAV_j, \dots, UAV_N$ are shown first from a top-down view. On the right, there are two zoomed-in views. First, depicting how the RIS is mounted on the underside of the UAV. Second depicting the Receiver with antennas $1, \dots, N$.

ter is located at an unknown position $\mathbf{p}_T = (x_T, y_T, z_T) \in \mathbb{R}^3$ and emits an omnidirectional wideband signal. We assume the transmitter is low to the ground. A centralized receiver station with N independent antennas and receiver chains is located at $\mathbf{p}_R = (0, 0, 0)$. For simplicity, we assume that all receiving antennas are located at $\mathbf{p}_R$, in reality, these would be set up relatively close together, and the correct position should be used.

A swarm of N UAVs, indexed by $i = 1, \dots, N$, is deployed in the airspace. Each UAV_i carries a square RIS _{i} consisting of $M \times M, M > 2, M \in \mathbb{N}$ reflecting elements. By design, every receiver antenna i is aimed at RIS _{i} such that it receives only the signal from RIS _{i} .

The set of nominal UAV positions is denoted by $\mathcal{P} = \{\mathbf{p}_1, \dots, \mathbf{p}_N\}$, where $\mathbf{p}_i = (x_i, y_i, z_i)$ represents the nominal position of UAV_i , in other words, where the system assumes UAV_i is. Due to positioning inaccuracies, the true position of each UAV_i is modeled as

$$\tilde{\mathbf{p}}_i + \boldsymbol{\epsilon} = \mathbf{p}_i, \quad (1)$$

where the positioning error is normally distributed as $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \text{diag}(\sigma_x^2, \sigma_y^2, \sigma_z^2))$, capturing uncertainty arising from GNSS or relative positioning mechanisms.

We assume that the positions of the transmitter, UAVs and receiver do not change during the localization steps.

For each reflector path via RIS _{i} , the true geometric distances between transmitter and RIS _{i} and RIS _{i} and receiver are respectively:

$$d_{Ti} \triangleq \|\mathbf{p}_T - \tilde{\mathbf{p}}_i\|, \quad (2)$$

$$d_{iR} \triangleq \|\mathbf{p}_R - \tilde{\mathbf{p}}_i\|. \quad (3)$$

The corresponding true propagation delays between transmitter and RIS _{i} and RIS _{i} and receiver are, respectively:

$$\tau_{Ti} \triangleq \frac{d_{Ti}}{c}, \quad (4)$$

$$\tau_{iR} \triangleq \frac{d_{iR}}{c}. \quad (5)$$

where c stands for the speed of light. Whereas the assumed propagation delay between RIS _{i} and receiver, computed using $\mathbf{p}_i$ is

$$\hat{\tau}_{iR} \triangleq \frac{\|\mathbf{p}_R - \mathbf{p}_i\|}{c}. \quad (6)$$

The total delay of the cascaded path via reflector _{i} is

$$\tau_i \triangleq \tau_{Ti} + \tau_{iR}. \quad (7)$$

B. CHANNEL MODEL

Based on the geometric model, the cascaded propagation path for RIS _{i} consists of a transmitter to RIS channel and a RIS to receiver channel. As both channels depend on the true UAV position, $\tilde{\mathbf{p}}_i$, expressed in Equation 1, we define the corresponding channels as follows. We use a high-gain small 3 dB beamwidth antenna for every receiver input aimed at the respective UAV. Since the UAVs are airborne and the transmitter is assumed ground-based, we can suppress a potential LoS path between transmitter and receiver. As multipath is caused by objects on the ground, we are able to suppress any first-order reflections, any second-order reflections are assumed negligible. By not assuming the existence of a LoS path between the transmitter and the receiver, our method will still be able to localize the transmitter in the absence of a LoS path. We also assumed that the transmitter, UAVs, and receiver are static during signal capture, hence there will be no Doppler shift.

TABLE 2. Notation used throughout the paper.

Symbol	Description	Units
c	Speed of light	m/s
f_c	Carrier frequency	Hz
f_s	Sampling frequency	Hz
$\mathbf{p}_R$	Receiver position (origin)	m
$\mathbf{p}_T$	True transmitter position	m
$\hat{\mathbf{p}}_T$	Estimated transmitter position	m
$\mathbf{p}_i$	Nominal position of RIS/UAV i	m
$\tilde{\mathbf{p}}_i$	True position of RIS/UAV i	m
ϵ	UAV positioning error vector	m
$\mathcal{P}$	RIS/UAV position set	m
N	Number of RIS/UAV/Antennas	—
M^2	Number of RIS elements	—
$x_T[n]$	Transmitted discrete-time signal	—
$y_i[n]$	Received signal via reflector i	—
$\mathcal{Y}$	Received signals set	—
$w_i[n]$	Additive noise at antenna i	—
$\mathbf{h}_{Ti}$	Channel from transmitter to RIS i	—
$\mathbf{h}_{iR}$	Channel from RIS i to receiver	—
α_{Ti}	Path gain (Tx $\rightarrow$ RIS i)	—
α_{iR}	Path gain (RIS $i \rightarrow$ Rx)	—
d_{Ti}	Distance (Tx $\rightarrow$ RIS i)	m
d_{iR}	Distance (RIS $i \rightarrow$ Rx)	m
Φ_i	RIS phase shift matrix	—
g_i	Cascaded channel via reflector i	—
Δn_{ij}	Relative delay in samples	samples
$\Delta_{ij}^{\text{comp}}$	Compensated time difference	s
$\ \cdot\ $	Euclidean norm	—
$(\cdot)^*$	Complex conjugate	—
$\text{diag}(\cdot)$	Diagonal matrix operator	—

The channel from the transmitter to RIS $_i$ is denoted by $\mathbf{h}_{Ti} \in \mathbb{C}^{M^2 \times 1}$. The complex baseband channel representation is given by

$$\mathbf{h}_{Ti} = \sqrt{L(d_{Ti})} e^{-j\frac{2\pi}{\lambda} d_{Ti}} \mathbf{a}_{\text{RIS}}(\theta_{Ti}, \phi_{Ti}), \quad (8)$$

where $L(d)$ denotes the large-scale path-loss function that can be calculated as $L(d) = \left(\frac{\lambda}{4\pi d}\right)^2$, and $\mathbf{a}_{\text{RIS}}(\theta_{Ti}, \phi_{Ti})$ is the RIS array response vector corresponding to the elevation and azimuth angles of arrival (θ_{Ti}, ϕ_{Ti}) .

Similarly, the channel from RIS $_i$ to the receiver antenna associated with path i is modeled in the RIS element domain as $\mathbf{h}_{iR} \in \mathbb{C}^{M^2 \times 1}$, given by

$$\mathbf{h}_{iR} = \sqrt{L(d_{iR})} e^{-j\frac{2\pi}{\lambda} d_{iR}} \mathbf{a}_{\text{RIS}}(\theta_{iR}, \phi_{iR}), \quad (9)$$

where (θ_{iR}, ϕ_{iR}) are the elevation and azimuth angles corresponding to the departure direction from RIS $_i$ towards the receiver.

The effective cascaded channel gain observed at the receiver for the path reflected by RIS $_i$ is expressed as

$$g_i = \mathbf{h}_{iR}^H \Phi_i \mathbf{h}_{Ti}, \quad (10)$$

where $\Phi_i = \text{diag}(\beta_{i,1} e^{j\theta_{i,1}}, \dots, \beta_{i,M^2} e^{j\theta_{i,M^2}}) \in \mathbb{C}^{M^2 \times M^2}$ is the RIS reflection matrix and $\beta_{i,n} \in [0, 1]$ and $\theta_{i,n} \in [0, 2\pi)$ denote

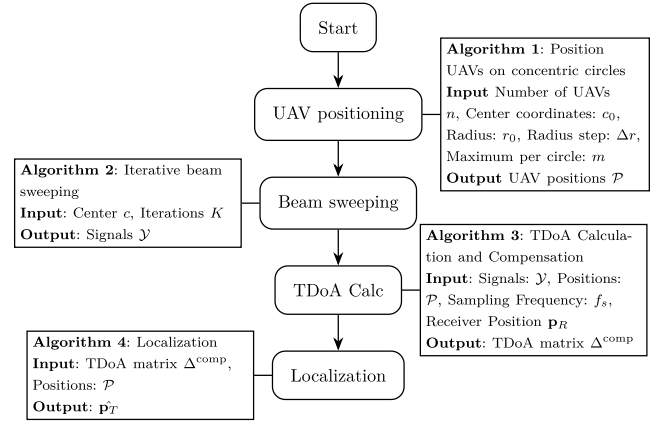


FIGURE 2. Localization algorithm flowchart.

the reflection amplitude and phase shift of the n -th reflecting element, respectively. Unless stated otherwise, we assume ideal unit-modulus reflection such that $\beta_{i,n} = 1$ for all n . During the signal acquisition step explained in Section IV, Φ_i is computed based on the positions of the reflector and receiver and an initialization value for the transmitter position (We use (0,0,0) as other values had no effect on the results). Since these positions are relative to the reflector, they can be precomputed and stored in a codebook.

C. SIGNAL MODEL

For each RIS $_i$, the receiver observes a reflected signal path with propagation delay τ_i and cascaded channel gain g_i as defined in the geometric and channel models. The discrete-time propagation delay in samples can be expressed as

$$n_i \triangleq \lfloor f_s \tau_i \rfloor \quad (11)$$

where f_s is the sampling frequency of the receiver.

Let $x_T[n]$ denote the transmitted discrete-time baseband signal, n denotes the discrete-time index. The transmitted signal is assumed to be sufficiently wideband to allow for time-domain delay resolution. Then the received discrete-time signal corresponding to the path reflected by RIS $_i$ is

$$y_i[n] = g_i x_T[n - n_i] + w_i[n] \quad (12)$$

where $w_i[n] \sim \mathcal{CN}(0, \sigma_w^2)$ denotes additive complex Gaussian noise.

IV. METHODOLOGY

This section provides a thorough explanation of the algorithms used for localization. We consider four main steps: (A) Reflector Positioning (B) Signal Acquisition (C) TDoA Estimation (D) Localization. Figure 2 gives an overview of these steps in a flowchart with the inputs and outputs of each associated algorithm. In the following sections, we will explain each step.

A. REFLECTOR POSITIONING

The goal of proper reflector positioning is two-fold: we must minimize Geometric Dilution of Precision (GDOP) while maximizing the RSS given N UAVs equipped with RISs. Since there is too little a priori information about

the transmitter, we position the UAV based on a predefined geometry. We use the 3D dome geometry as described in [23]:

$$\mathbf{p}_i = \begin{cases} (x_c, y_c, z_0 + \Delta_z), & i = 0 \\ \left(x_c + r_0 \cos \frac{2\pi(i-1)}{N-1}, \right. \\ \left. y_c + r_0 \sin \frac{2\pi(i-1)}{N-1}, \right. \\ \left. z_0 \right), & i = 1, \dots, N-1 \end{cases} \quad (13)$$

This geometry was chosen based on its minimization of GDOP as calculated in [23] and among the other methods: planar polygon, stacked polygon and 3D helix, also described in [23], the 3D dome geometry performed best for our use case.

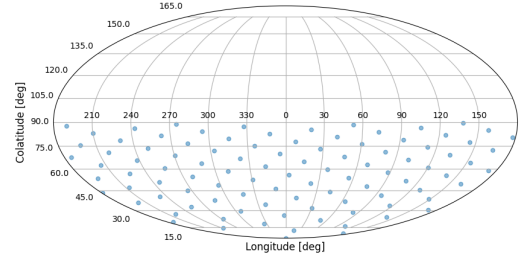
The geometry can be characterized by the following parameters: $(c = (x_c, y_c, z_c), z_0, \Delta_z, r_0, N)$ as shown in Equation (13). These parameters must be optimized in order to get the highest localization accuracy. However, since no range estimate for the transmitter is available a priori a conservative guess must be made that minimizes GDOP, without failing the signal acquisition step.

B. SIGNAL ACQUISITION

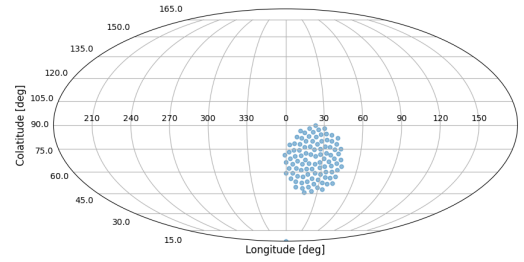
In the signal acquisition step, we employ an iterative beam-sweeping algorithm [24] to configure each RIS_i such that it redirects the signal from the transmitter towards antenna $_i$ at the receiver. The goal is to configure each RIS such that the receiver has enough input power in order to compute the time difference between two incoming signal paths. By design, each antenna $_i$ receives the transmitted signal from each distinct RIS_i without interference from other RIS. In practice, this would require high-gain directional antennas, or preferably, beamforming arrays for which the configuration is trivial, as the UAV location is known.

In order to configure the RIS, we require a phase profile Φ_i to reflect energy from coordinates $\mathbf{a}$ to $\mathbf{b}$, relative to the RIS. Ideally, $\mathbf{a} = \mathbf{p}_T$ and $\mathbf{b} = \mathbf{p}_R$, however, only $\mathbf{p}_R$ is known a priori. We seek $\mathbf{a}$ such that $\|\mathbf{a} - \mathbf{p}_T\| < \epsilon_{\text{xcorr}}$, where ϵ_{xcorr} is sufficiently small such that the resulting path loss remains within tolerable range for successful cross-correlation.

We employ an iterative beam-sweeping approach that optimizes $\mathbf{a}$ based on received power at the receiver. Each RIS_i is located at $\mathbf{p}_i = (x_i, y_i, z_i)$. During each test in our algorithm, we configure each RIS_i with coordinates $(\mathbf{a}_{\text{test}}, \mathbf{p}_R)$ and measure the received power. Every iteration, we test q points over a circular patch centered about direction $\mathbf{d}$ and aperture α . Each subsequent iteration we update $\mathbf{d}$ to the optimal point from the previous iteration. α is reduced by a set factor Δ_α , narrowing the search space. In the first iteration, $\mathbf{d}$ is set to $(0, 0, -z_i)$, i.e. straight down from the RIS and α is set to π radians, covering the entire lower hemisphere. q should be set based on the beamwidth, which is dependent on number of elements in the RIS, which in turn is dependent on the frequency of the signal and based on the required ϵ_{xcorr} . The number of iterations required is dependent on the required ϵ_{xcorr} . Intuitively, a transmitter at a larger range requires more precise aiming, so ϵ_{xcorr} will be smaller.



(a) Iteration one of the beam sweeping algorithm, $\alpha = \pi$



(b) Iteration two of the beam sweeping algorithm, $\alpha = \pi/8$

FIGURE 3. Two iterations of the beamsweeping algorithm showing $q = 100$ points.

Algorithm 1 Beam Sweeping: Iterative Beam Search via Hemisphere Sampling. $\mathcal{O}(N \cdot K)$

Input : number of points q , iterations I , shrink factor Δ_α , height z

Output: Direction of highest received power $\mathbf{d}$

Initialize $\mathbf{d} = (0, 0, -z)$, $\alpha = \pi$, $\text{rss} = []$

for $i = 1$ **to** I **do**

$\mathcal{Q} \leftarrow \text{SamplePoints}(q, \mathbf{d}, \alpha)$;

for $i = 1$ **to** N **do**

 ConfigureReflector($\mathbf{q}_i$);

$\text{rss}_i \leftarrow \text{MeasureRSS}()$;

end

$i^* \leftarrow \arg \max_i \text{rss}_i$;

$\mathbf{d} \leftarrow \mathbf{q}_{i^*}$;

$\alpha \leftarrow \alpha \Delta_\alpha$;

end

return $\mathbf{d}$;

We tune the parameters q , the reduction factor Δ_α , and the number of iterations to optimize this method. We formalize this in Algorithm 1. The SamplePoints method produces a circular patch on a hemisphere given the description above. Figures 3a and 3b each show the points under test for one iteration of the beam sweeping algorithm, as given by the SamplePoints method.

C. TDOA ESTIMATION

This section explains the process of estimating the TDoA. In the previous section, we have already configured the RIS phase matrices Φ_i to maximize the RSS.

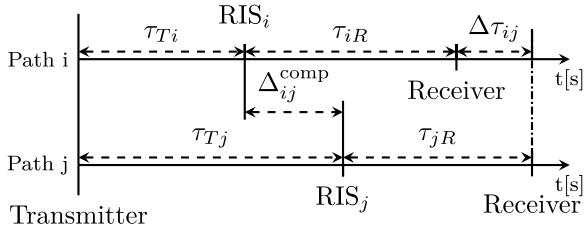


FIGURE 4. One-dimensional signal delay model: x-axis represents time t , the vertical axis indexes the signal path. τ_{Ti} is transmitter $\rightarrow$ RIS _{i} delay, τ_{iR} is RIS _{i} $\rightarrow$ receiver delay, $\Delta\tau_{ij} = (\tau_{Ti} + \tau_{iR}) - (\tau_{Tj} + \tau_{jR})$ is measured by cross correlating signals $y_i[t]$ and $y_j[t]$. $\Delta_{ij}^{\text{comp}}$ is the compensated TDoA for use in Algorithm 3:
 $\Delta_{ij}^{\text{comp}} = \Delta\tau_{ij} - (\hat{\tau}_{iR} - \hat{\tau}_{jR})$.

In this stage of the localization procedure, we estimate the relative delay between the signals corresponding to RIS _{i} and RIS _{j} via cross-correlation. The estimated discrete delay difference in the number of samples between paths i and j is

$$\hat{\Delta}n_{ij} = \arg \max_{\ell} \sum_n y_i[n] y_j^*[n - \ell] \quad (14)$$

where $y_i[n]$ and $y_j[n]$ are defined in Section III-C. The corresponding TDoA estimate in seconds is

$$\hat{\Delta}\tau_{ij} = \frac{\hat{\Delta}n_{ij}}{f_s}. \quad (15)$$

The accuracy of $\hat{\Delta}\tau_{ij}$ depends on f_s .

To apply standard TDoA localization techniques, we require the delay difference between the transmitter-to-RIS paths,

$$\Delta_{ij}^{\text{standard}} = \tau_{Ti} - \tau_{Tj}. \quad (16)$$

Since the measured delay difference $\hat{\Delta}\tau_{ij}$ includes both the transmitter-to-RIS and RIS-to-receiver propagation components, we compensate for the latter to isolate the transmitter-related delay as follows (using Eq. (7)):

$$\begin{aligned} \hat{\Delta}_{ij}^{\text{standard}} &= \hat{\Delta}\tau_{ij} - (\hat{\tau}_{iR} - \hat{\tau}_{jR}) \\ &= \hat{\Delta}_{ij}^{\text{comp}}. \end{aligned} \quad (17)$$

We emphasize that $\hat{\tau}_{iR}$ is used here, since we compute the delay based on the set UAV position $\mathbf{p}_i$ and not the true position $\tilde{\mathbf{p}}_i$ since the latter is unknown to the system.

We collect all estimated and compensated delay differences $\hat{\Delta}_{ij}^{\text{comp}}$ for $i < j$ into the set $\hat{\Delta}^{\text{comp}}$. Figure 4 illustrates the delay compensation principle. We formalize these steps in Algorithm 2 to compute $\hat{\Delta}^{\text{comp}} = \hat{\Delta}_{ij}^{\text{comp}} \forall i, j \mid i < j$. Using $\hat{\Delta}^{\text{comp}}$ we proceed to the localization step.

In practice, the delay estimation in Equation (14) is done using a Fast Fourier Transform (FFT). Dividing the FFT size by the sampling rate gives us the coherent integration time. This is the minimum time our UAV would need to be static in order for it to not affect the measurement. In Table 3, we assume a default sampling rate of 300 MS/s. With a large FFT of 16 million points, the coherent integration time would be equal to ± 55 milliseconds. This timeframe is short enough to consider the UAV static. This also requires phase-coherent receivers which is done by sharing a local oscillator between multiple receivers, we refer the reader to [25] for more information on setting up a phase-coherent

Algorithm 2 Compensated Time Deltas From Pairwise Cross-Correlations. $\mathcal{O}(N^2 \cdot K)$

Input: Signals $\mathcal{Y}$, UAV Positions $\mathcal{P}$, Receiver position $\mathbf{p}_R = (0, 0, 0)$, sampling frequency f_s , propagation speed c

Output: Matrix $\hat{\Delta}^{\text{comp}}$ of compensated time deltas

Initialize $\hat{\Delta}^{\text{comp}}$ as an $N \times N$ zero matrix;

for $i = 1$ to N do

for $j = i + 1$ to N do

// all unique pairs i, j

$$\hat{\Delta}n_{ij} \leftarrow \arg \max_k \sum_n y_i[n] \cdot y_j^*[n - k];$$

// find delay

$$\hat{\Delta}\tau_{ij} \leftarrow \frac{\hat{\Delta}n_{ij}}{f_s};$$

// convert to time domain

$$\hat{\tau}_{iR}, \hat{\tau}_{jR} \leftarrow \frac{\|\mathbf{p}_R - \mathbf{p}_i\|}{c}, \frac{\|\mathbf{p}_R - \mathbf{p}_j\|}{c};$$

// compute compensation

$$\hat{\Delta}^{\text{comp}}(i, j) \leftarrow \hat{\Delta}\tau_{ij} - (\hat{\tau}_{iR} - \hat{\tau}_{jR});$$

end

end

return $\hat{\Delta}^{\text{comp}}$;

Algorithm 3 Location Estimation. $\mathcal{O}$ Depends on Used Optimizer

Input: Compensated time differences $\hat{\Delta}^{\text{comp}}$, RIS positions $\mathcal{P}$

Output: Estimated transmitter position $\hat{\mathbf{p}}_T$

Initialize candidate position $\mathbf{p} = (0, 0, 0)$;

Solve

$$\hat{\mathbf{p}}_T = \arg \min_{\mathbf{p}} \sum_{i < j} \left(f_{ij}(\mathbf{p}) - c \hat{\Delta}_{ij}^{\text{comp}} \right)^2,$$

where

$$f_{ij}(\mathbf{p}) = \|\mathbf{p} - \mathbf{p}_i\| - \|\mathbf{p} - \mathbf{p}_j\|.$$

using a standard nonlinear optimizer (e.g. L-BFGS-B);

return $\hat{\mathbf{p}}_T$;

multi-receiver system, note that this is only feasible when the receivers are co-located.

D. LOCALIZATION

Given the compensated TDoA measurements $\hat{\Delta}^{\text{comp}}$, the transmitter position $\hat{\mathbf{p}}_T$ is estimated using a least-squares formulation. Specifically,

$$\hat{\mathbf{p}}_T = \arg \min_{\mathbf{p}_T} \sum_{i < j} \left(f_{ij}(\mathbf{p}_T) - c \hat{\Delta}_{ij}^{\text{comp}} \right)^2, \quad (18)$$

where

$$f_{ij}(\mathbf{p}_T) = \|\mathbf{p}_T - \mathbf{p}_i\| - \|\mathbf{p}_T - \mathbf{p}_j\|. \quad (19)$$

Geometrically, this corresponds to finding the intersection point of one of the sheets of a hyperboloid drawn between

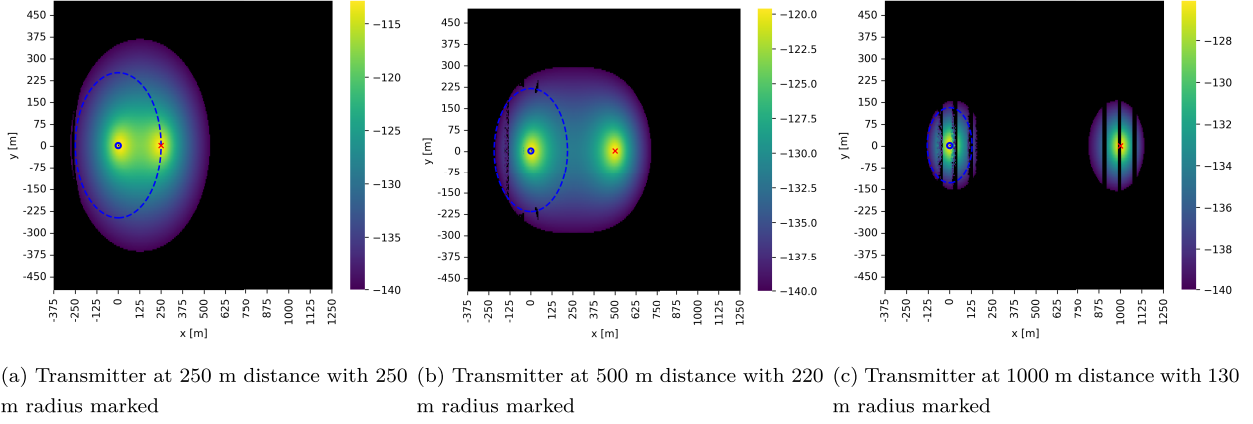


FIGURE 5. Heatmap of the path loss at each possible RIS position. The blue O and red X mark the receiver and transmitter, respectively. The black area marks the positions where a RIS has less than the -140 dB channel as derived in Section V-A. We note that the missing lines in Figures (b) and (c) are caused by fp32 rounding errors in the simulation.

TABLE 3. Parameters used for simulations. The default parameters are marked in bold.

	Low	Medium	High
Transmitter distance [m]	250	500	1000
Sampling rate [MS/s]	150	300	600
Position error [m]	0.01	0.1	0.5
Z-height [m]	10	25	50
Z-step [m]	10	25	50
Radius [m]	50	100	200
Number of reflectors	4	6	10
Frequency [GHz]	1.5	3.5	28
RIS elements ¹ [elements]	5x5	11x11	93x93
Random seed	0	...	1000

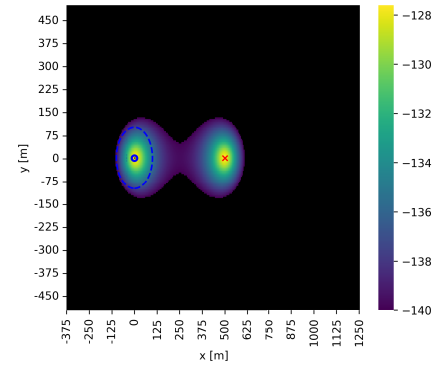


FIGURE 6. Example coverage area when an isotropic antenna is used with a transmitter at 500 m distance with 100 m radius marked.

focal points $\mathbf{p}_i, \mathbf{p}_j$, where each point $\mathbf{p}$ has a constant difference of distances to $\mathbf{p}_i$ and $\mathbf{p}_j$.

We formalize this in Algorithm 3.

E. SUMMARY OF METHODOLOGY

In traditional TDoA localization systems, geographically distinct multiple receivers are necessary, similar to the RIS in our system. A traditional system directly estimates $\tau_{Ti} - \tau_{Tj}$, $i \neq j$ for localization use. In our system, we position the UAVs as if they were geographically distinct receivers (Equation (13)) to redirect the signal of interest to a single geographical location (Algorithm 1) to avoid synchronizing multiple distributed receivers, which can pose significant challenges in ad-hoc scenarios. Due to this redirection, we need to compensate for this extra travel time as shown in Equation (17).

After calculating the compensated TDoA (Algorithm 2) for each pair $i, j \mid i < j$ of RIS, we can localize the transmitter using known TDoA methods.

As our model includes several sources of error, the sheets of the hyperboloids will not intersect perfectly at the transmitter position. We use a standard non-linear optimization algorithm to find a point that minimizes the point-to-curve distance for the set of hyperbolas, i.e. it solves the problem posed in Eq. (18) (Algorithm 3).

V. PERFORMANCE ANALYSIS AND RESULTS

In this section, we show the results of the experiments and analyze the performance of our system. In these experiments, we tested several combinations of parameters. We summarize these values in Table 3.

The default parameters are chosen for the following reasons. The sampling rate of 300MS/s is capable by a high-end Software Defined Radio (SDR), such as an USRP X410 [26]. The position error of 0.1 meter or 10 centimeter for the UAV is achievable by, for example, a Real-Time Kinematics (RTK)-equipped UAV [27], in the case that the objective is to localize a Global Positioning System (GPS) jammer, other methods must be used. The positioning algorithm parameters were empirically chosen. The frequency is used for GNSS, which is often victim of jamming. Finally, the transmitter distance of 500 meters was chosen as a representative example distance.

A. RIS LOCATION FEASIBILITY

In this experiment, we tested the possible locations an RIS can be positioned to have the minimal path gain required for successful cross-correlation of the two signals. We tested this with a transmitter at {250, 500, 1000} meters. We also show the importance of using a directional antenna at the receiver to receive the signal reflected from the RIS. However, first we

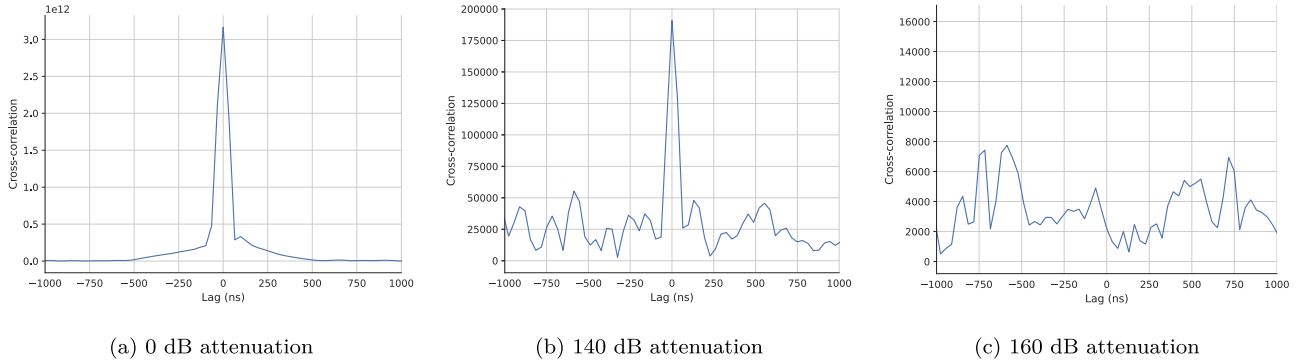


FIGURE 7. Cross-correlation plots of a wide-band noise signal sent from one USRP X410 via a 2-way power-splitter to a second USRP X410. Note that the Y-scale is orders of magnitude different between the figures (a), (b) and (c).

must find the baseline minimal input power for our receiver, in order for us to get usable results from the cross-correlation computation. Once that number is established, we compute the area where RISs can be positioned such that a transmitter at {250, 500, 1000} meters transmitting with 30 dBm of power can be reliably received, based on the previously found baseline minimal input power number.

1) BASELINE RECEIVER INPUT POWER

To quantify the experiment described in Section V-A, we measured the minimum input power required for the TDoA measurement and derive the minimal path gain from that. For this experiment, we used two USRP X410 to simulate a 30 dBm transmitter and a receiver. We chose to use this type of SDR for their high bandwidth capability and phase coherence between channels. We were able to add a maximum of 140 dB of attenuation in the signal path, beyond that, the cross-correlation computation yielded unusable results. We show this in Figures 7a, 7b and 7c. This gives us a lower bound of -140 dB of minimum path gain.

2) RIS LOCATION FEASIBILITY EXPERIMENT

This experiment uses the Sionna framework by NVIDIA [28] to simulate the path from transmitter $\rightarrow$ RIS $\rightarrow$ receiver and calculate the gain for each possible RIS position within fixed bounds. We chose the bounds such that a RIS placed outside of the given bounds can never achieve the required minimum path gain, calculated from the free space path loss model. The maximum size of the RIS depends on the payload capacity of the UAV. To show that our work can work on low payload capacity UAVs, we assume a RIS of 50 cm $\times$ 50 cm, which translates to a 4×4 element RIS with $\lambda/2$ spacing at a carrier frequency of 1.2 GHz. Transmitters were positioned at 250, 500, and 1000 meters from the receiver.

Figure 5 shows the resulting heatmaps, the colored area shows the highest possible gain when an RIS is at that position. Outside of the colored area, the path gain is less than -140 dB. Given that only the receiver location is known a priori, we can model an approximate radius around the receiver where the RIS can feasibly be, as is shown by the dashed blue circle in Figure 5.

In Figure 6, we show how using an isotropic antenna at the receiver has a negative effect on the potential RIS locations.

We compare this with the blue dashed circle of Figure 5b, it is $\pm 4.8\times$ larger than that of Figure 6, showing the importance of using a high-gain narrow-beam antenna.

B. SIGNAL ACQUISITION PERFORMANCE

In this experiment we test the performance of the signal acquisition algorithm based on beam-sweeping. As an upper-bound benchmark, we compare our search method against an oracle that knows the transmitter location exactly. Results are reported over 1000 random seeds. The system parameters used are the parameters in bold in Table 3.

In Figure 8, we show the Empirical Cumulative Distribution Function (ECDF) of the path gain difference between the oracle and the beam-sweeping algorithm. A difference of 0 indicates alignment between the oracle and beam-sweeping algorithm, negative values indicate a performance gap, where the beam-sweeping algorithm is worse than the oracle. We show that our method closely approximates the oracle. Specifically, the median gap is 0.024 dB, while 95% of samples are within 0.126 dB of the oracle. This result shows that the proposed method incurs a negligible loss in path gain over the oracle method.

C. 3D LOCALIZATION ALGORITHM PERFORMANCE

With the knowledge of the feasible range for reflector placement from Section V-A, we can tune the geometry from Equation (13) for optimal performance with different transmitter ranges. However, in a practical implementation of this algorithm, the transmitter range is unknown. One method for solving the unknown range issue is using a multi-iteration approach, where we start with a conservative geometry and work our way to a more accurate geometry, we consider this system-level design aspect as part of future work.

In the rest of this section, we will discuss the results for the parameters given in Table 3. We refer to the numbers in bold as our default parameters. Later, we go into more detail about the effect of varying each parameter.

We obtained the results by testing each combination of parameters for 1000 different random seeds. The randomizer affects the position of the transmitter and the self-localization error of the UAV. To quantify performance, we measured the Root Mean Square Error (RMSE) between the true location p_T and the estimated location $\hat{p}_T$.

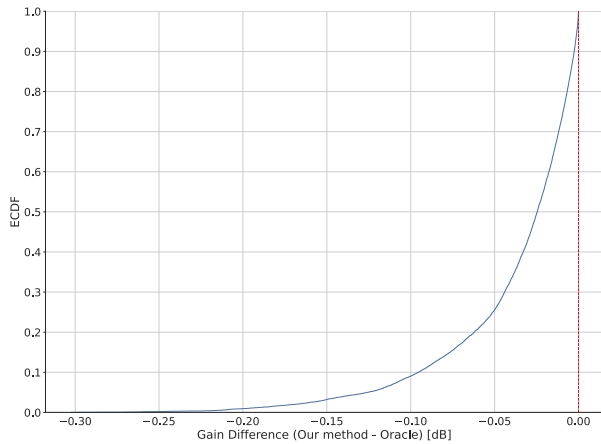


FIGURE 8. ECDF Curve comparing oracle-based path loss to beam-sweeping. Red dashed line indicated the 0 dB mark: Intuitively, our method has a strictly worse path than the oracle method.

Figure 9 shows the ECDF of the RMSE by number of reflectors using the default parameters. From these data, we see that for four reflectors, the system has poor performance due to high GDOP.

It is expected that the return on investment of adding more reflectors decreases significantly after six reflectors. In summary, with six reflectors or more, 90% of our estimations have an error of less than 26 meters with a transmitter at 500 meter.

1) TUNING PARAMETERS

Next, we discuss how each parameter has an effect on the localization performance. Figure 10 shows these results. Each subplot varies a single parameter and shows its effect on the performance. Each box shows the quartiles of measured RMSE; the whiskers show the rest of the distribution. We remove outliers using the inter-quartile range method.

First, we vary the **transmitter distance**. Naturally, GDOP increases as the transmitter gets further away from the reflectors relative to the receiver. This causes the results for 6 reflectors, with a transmitter at 1000 meter, to be much worse than at 250 meter or 500 meter. With 10 reflectors, the system is much more robust. We can further counteract GDOP by tuning the parameters in Equation (13).

Second, a higher **sampling rate**, given enough bandwidth of the signal, also increases performance. From the formula: $l_d = \frac{c}{f_s} \times N_d$ with c the speed of light, we see that the number of delay samples measured N_d is proportional to the signal travel distance l_d , if $N_d = 1$ we get the inherent accuracy of the system which is inversely proportional to f_s , so a higher sampling frequency equals better range accuracy. This increase in range accuracy leads to a decrease in localization error. With 600 MS/s and 10 reflectors, the maximum error is less than 20 meter.

Third, the **positioning error** has a large effect on the localization performance. Due to the setup, the TDoA measurement is based on the true position $\tilde{\mathbf{p}}$, whereas compensation happens via the nominal position $\mathbf{p}$. We see that with a positioning error ϵ of 0.5 meter, our maximum

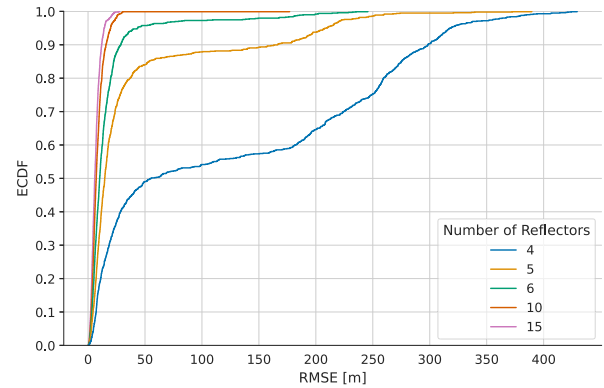


FIGURE 9. RMSE CDF plot per number of reflectors with the bold parameter set.

error raises to 80 meter, whereas if the positioning error is 0.01, the maximum error is only 12 meter. This result shows the importance of using a highly accurate positioning method for the UAVs, for example using RTK to further enhance Global Navigation Satellite System (GNSS)-based positioning or other means of relative positioning to the receiver. We give further evidence of why high-accuracy positioning of the UAVs is necessary in Figure 11, where we use the default parameters and vary the positioning error further than in Figure 10. At higher positioning error, the localization accuracy drops to an unusable 1200 meter.

Next, we discuss the parameters of Equation (13): the minimal $\mathbf{Z}$ of the UAVs, the **Z-step** of UAV₀ and, the **radius** of the UAVs. The minimal $\mathbf{Z}$ of the UAVs mostly affects the signal acquisition performance, if the UAV is lower to the ground, the incidence angle to RIS becomes lower as well, making it harder for the RIS to reflect the signal. We see this in the low accuracy with 6 reflectors at 10 meter height, whereas with 10 reflectors, we compensate for this loss. From the raw data, when using 6 reflectors, on average 3.5 reflectors had successful signal acquisition, whereas with 10 reflectors, an average of 9.7 reflectors were available for localization. Barring the effect of signal acquisition, the minimal $\mathbf{Z}$ has little effect on the accuracy. The $\mathbf{Z}$ -step however, does have an effect on the localization, specifically on accuracy in the $\mathbf{Z}$ -axis. Since UAV₀ is the only reflector that is out of the plane, it is crucial in resolving the $\mathbf{Z}$ -coordinate of the transmitter. As a larger $\mathbf{Z}$ -step decreases GDOP, it increases localization accuracy. We see that increasing the radius has the largest effect on the localization accuracy. A radius of 50 meters has a mean error of 23 meter, whereas using a radius of 200 meter the mean error decreases to 4 meter.

Finally, the carrier **frequency** has little effect on the localization accuracy. As we previously assumed that we know what the working frequency is, we outfit the UAV with a RIS for that frequency range. It is known that signals of higher frequency are attenuated more than lower frequency signals, however this is compensated by the gain of having more elements on the RIS. We do note that having more elements increases the complexity of the RIS phase profile codebook, but it can be precomputed.

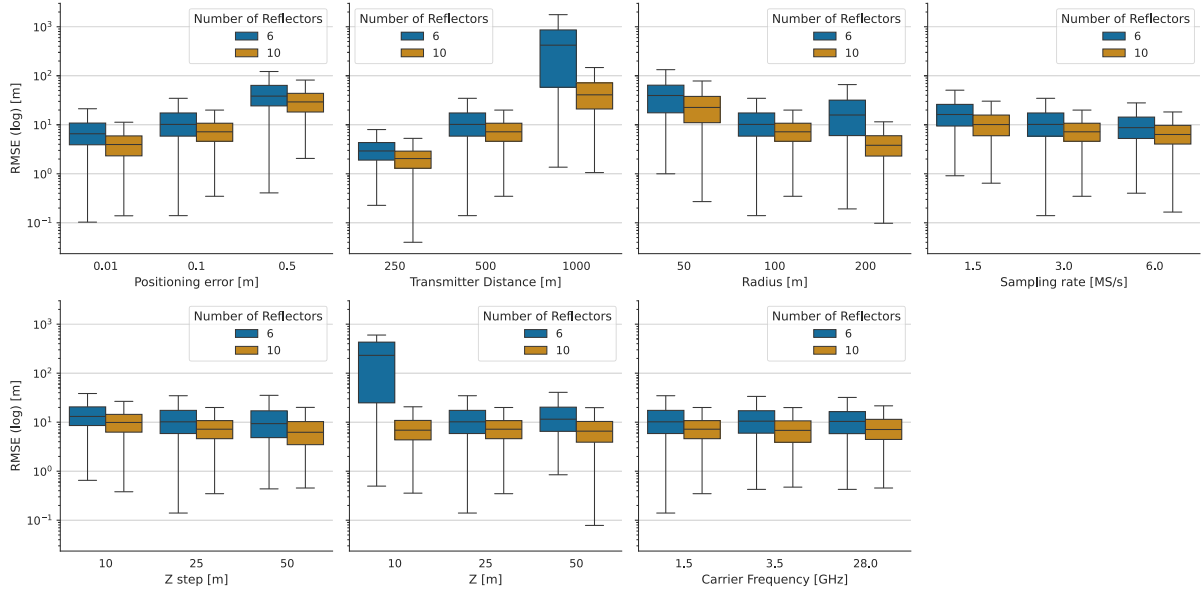


FIGURE 10. Logarithmic boxplots showing the effect of varying each parameter in isolation with either 6 or 10 reflectors. Outliers removed based on the interquartile range.

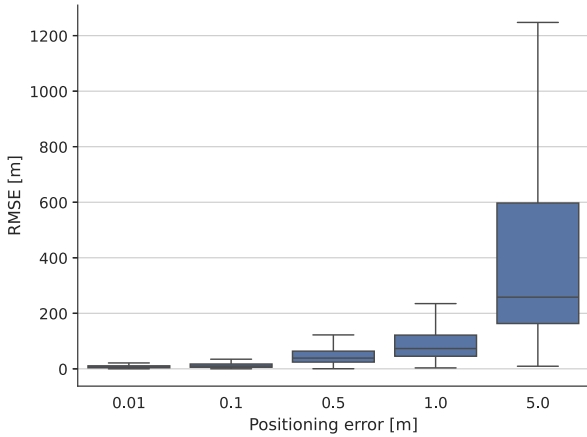


FIGURE 11. RMSE versus UAV positioning error using the realistic parameter set with 6 reflectors.

VI. DISCUSSION

This section discusses the obtained results and highlight potential improvements and extensions of the proposed system. We first revisit the key assumptions made in this study and discuss their implications.

First, we have assumed that the transmitter is static. In more realistic scenarios, it is possible that the transmitter is moving, which would induce a Doppler shift on the received signal. That Doppler shift will need to be accounted for in future work. Another problem with a moving transmitter is the limited time window in which the localization can happen, which requires a dynamic system to track the transmitter.

Second, we have assumed that the reflectors are perfectly stationary, in reality, UAVs are not able to hover perfectly still. We assume that the relatively slow drift of an imperfectly hovering UAV would not impact the measurements, however, further work is necessary to substantiate this claim.

Third, not all configurations of the proposed algorithms are always possible. For example: from the results of Section V-A, we see that for a transmitter at 500 meters, the maximum reliable radius for the reflectors is ± 220 meters. If the parameters are such that a reflector is placed outside of this radius, it would not aid in localization. Since the transmitter range is not known beforehand, a more dynamic method of placing the reflectors is necessary to optimize performance. We emphasize that all results shown in Figure 10 are attainable and have configurations such that no reflector is placed outside of this radius. We aim to work on the issues of moving transmitter, moving reflector, and moving receiver in dynamic scenarios in the future.

Fourth, for the signal acquisition step, we assumed there is only one transmitter at that frequency. This assumption is reasonable in some cases, e.g. GNSS jammers operating terrestrially, whereas the legitimate transmitters are space-borne or search-and-rescue in remote areas where the transmitter density is low. In transmitter-dense environments, our current method will not be able to home in on a singular, specific transmitter. Further work is necessary to devise a method that can find a specific signal.

Fifth, we assumed the RISs are ideal and do not suffer from the known limitations. We consider two main limitations that can affect our work, but for which further study is required to measure the true impact. (i) Physical RIS are limited to quantized phase shifts. That limits us to an integer number of reflection angles, however, we can potentially rotate the UAV to fine-tune the reflection angles. (ii) Physical RIS are not ideal reflectors and some losses are had. Those extra losses would equal a higher path loss which will limit our systems range. Further experiments are necessary to quantify the effects of physical RIS impairments.

Sixth, the current method uses only TDoA information. From the beam sweeping algorithm, we also have estimate angles of arrival which can also be put to use. In this work,

we focused on measuring the effectiveness of the TDoA information only. In subsequent work, we integrate the AoA at the RIS to boost localization accuracy further or decrease the number of reflectors necessary to attain usable accuracy.

Seventh, this work is based mostly on simulation work, with only the lower bound on path gain derived experimentally. In future work, we aim to use real hardware to test our findings.

VII. CONCLUSION

This work showed that UAV mounted RIS can redirect signals to a centralized multi-channel receiver for TDoA-based localization of arbitrary transmitters, such as jammers, by compensating for the extra delay added to the reflected signal.

We showed that with a limited sampling rate, error on UAV positioning and six reflectors, we have a worst-case error of 26 meter when the transmitter is at 500 meter distance. An optimally configured system with 10 reflectors achieves sub 10-meter-level accuracy, however at high transmitter distances or with insufficient reflectors, the system fails to locate the transmitter. By tuning the parameters of the reflector positioning algorithm, taking into account the maximum radius around the receiver, we can achieve this optimal configuration.

Future work will tackle more assumptions making the method more robust and extending it to a dynamic system where moving transmitters, reflectors, and receiver in complex environments with strong multi-path can be taken into account.

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