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Positioning of UAVs in Urban Environments Using Fusion of TDOA and AOA Data Based on Extended Kalman Filter

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Abstract

Unmanned aerial vehicles (UAVs) have been extensively deployed across a range of applications thank to their flexibility and low cost. While this expansion has significantly improved their operational efficiency and service capacity, it has also posed challenges for UAV supervision and management systems. To address these issues, this paper proposes a three-dimensional (3D) localization method that integrates time difference of arrival (TDOA) and angle of arrival (AOA) measurements based on the extended Kalman filter (EKF). Specifically, for AOA-based positioning, a uniform circular array (UCA) is employed to capture spatial signal characteristics, and the multiple-signal classification (MUSIC) algorithm is applied to precisely estimate the azimuth and elevation angles of incoming signals. In TDOA-based localization, a multipath signal separation and identification algorithm is implemented to enhance robustness against multipath propagation in complex environments. Subsequently, the TDOA and AOA measurements are fused using the EKF, where nonlinear measurement models are linearized via Jacobian matrices to improve computational efficiency and estimation accuracy. Finally, simulation results demonstrate that the proposed hybrid localization method outperforms existing positioning methods that rely solely on AOA or TDOA, achieving a positioning accuracy of approximately 5 m and an angular error within 3°, which is suitable for applications in multipath environments such as urban areas.

Keywords: angle of arrival estimation; time difference of arrival estimation; MUSIC algorithms; extended kalman filter; UAV positioning



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1. Introduction

In recent years, unmanned aerial vehicle (UAV) technology has advanced rapidly. Owing to their significant flexibility and line-of-sight (LOS) connectivity, UAVs have been widely applied to variable fields such as smart agriculture, infrastructure inspection, surveillance operations, and industrial automation [1–3]. As a key driver of the modern economy, the low-altitude sector is now experiencing rapid growth, which in turn has amplified the demand for efficient and reliable UAV control mechanisms. This need is particularly acute in complex urban environments, where dense structures and dynamic obstacles pose significant challenges to precise UAV positioning [4].

The localization of UAV using passive radio frequency (RF) techniques has been extensively studied. These methods are particularly effective in LOS environments, where

reliable signal propagation facilitates accurate positioning [5]. Numerous positioning methods have been proposed, including time-of-arrival (TOA)-based estimation [6], time difference-of-arrival (TDOA)-based positioning [7,8], and angle-of-arrival (AOA)-based positioning [9,10]. These techniques estimate UAVs' position by leveraging the time differences or angle of arrival received at multiple receivers. However, in practical application scenarios, these localization methods face various challenges such as multipath effects, noise interference, and hardware limitations, which can significantly degrade positioning accuracy.

To address the aforementioned issues, researchers have developed various techniques, including blind signal separation and high-resolution signal spectrum estimation. For instance, spatial smoothing methods can be employed to mitigate multipath effects, while high-resolution direction-finding algorithms, such as Multiple-Signal Classification (MUSIC) and Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), are utilized to enhance system robustness [11]. These approaches not only enable accurate estimation of signal arrival time but also significantly improve direction-finding accuracy and resolution, thereby improving overall positioning accuracy [12]. Specifically, the MUSIC algorithm is a typical subspace decomposition-based method, which is widely used in array signal processing for direction-of-arrival estimation of signals. It leverages the orthogonality between the signal and the noise subspaces to construct a spatial spectrum function, allowing for high-precision estimation of signal arrival angle of target signals [13].

Despite these advancements, positioning methods relying solely on AOA or TDOA face inherent limitations, such as the requirement for numerous base stations (BSs) and limited positioning accuracy. To overcome these drawbacks, the hybrid AOA-TDOA positioning method has been proposed. This approach not only reduces the number of BSs needed to locate a source in 3D space, but also enhances system robustness [14].

To effectively fuse diverse measurements such as AOA and TDOA, which are enabled by such hybrid systems, recursive estimation techniques such as the Kalman filter (KF) have been widely adopted. As a linear minimum-variance unbiased estimator, the KF recursively refines state estimates by leveraging system dynamics and observation models [15]. This capability allows it to optimally integrate distance information derived from TDOA with angle information obtained from AOA, thereby facilitating high-precision localization for UAV [16].

1.1. Related Work

Hybrid AOA-TDOA localization has seen considerable developments in recent years that have aimed to address the challenges of accurate positioning. Early foundational works focused on developing geometric and optimization frameworks. For instance, hybrid positioning methods were introduced to reduce infrastructure dependence by minimizing the number of BSs [17]. Subsequently, techniques like weighted least squares were proposed to efficiently fuse AOA and TDOA measurements for 3D localization, and simulation results demonstrated the effectiveness of the method in terms of root mean-squared error (RMSE) [18]. To specifically tackle UAV localization in complex non-line-of-sight (NLOS) scenarios, a method utilizing only three receivers for joint AOA-TDOA estimation was developed [19]. Furthermore, to overcome Global Navigation Satellite System limitations in urban UAV applications, an innovative 5G network-based positioning system was proposed in [20]. This system employs machine learning and clustering techniques to optimize base station management and selection, applies Taylor-series least squares for position refinement, and integrates AOA measurements to improve altitude estimation accuracy.

The above works have estimated AOA through distance measurements. Such methods are constrained by inherent limitations, including error propagation and limited angular resolution. To mitigate these issues, researchers have begun to adopt direct AOA estimation methods that employ uniform circular arrays (UCA) in combination with the MUSIC algorithm. This approach provides superior spatial discrimination and full-azimuth coverage. For example, the authors of [21] studied two beamspace eigenstructure-based algorithms, UCA-MUSIC and UCA-ESPRIT; derived asymptotic variance expressions for both element-space MUSIC and UCA-MUSIC; and substantiated the theoretical findings through comparative simulations. Similarly, the authors of [22] developed an SDR-based UAV localization system that utilizes a five-element UCA along with a MUSIC-based algorithm for AOA estimation.

Concurrently, the Kalman filter and its variants, particularly the extended Kalman filter (EKF), have been integrated into localization architectures to enhance robustness and enable dynamic tracking. To address TDOA estimation in environments where communication is poor, the authors of [23] employed a data-driven multiple-model Kalman filter for UAVs. For the specific problem of dynamic direction-of-arrival estimation, a more sophisticated strategy was introduced in [24], which combined a covariance-adaptive EKF with 2D MUSIC processing to improve accuracy and enable LOS identification. More recently, to achieve a fully GPS-independent solution, the system in [25] was developed. This method synergistically fuses MUSIC-based AOA estimates from two arrays through triangulation and further refines the location estimates with an EKF, a design that was ultimately validated experimentally against GPS data.

The above studies either do not employ an EKF for hybrid data fusion [17–20], or do not fully integrate both measurement types within the EKF’s state update model [23–25]. Therefore, a gap remains in the integration of direct, high-resolution UCA-based AOA estimation and TDOA measurements within an EKF framework for real-time UAV positioning. Our work directly addresses this gap by proposing an EKF-based hybrid positioning method that jointly processes AOA measurements (obtained from a UCA-MUSIC algorithm) and TDOA measurements (extracted via a dedicated multipath separation algorithm) within a single state estimation loop. A detailed comparison summarizing the novelty of our integrated approach against the existing literature is presented in Table 1.

Table 1. Comparison of the related works.

Ref.	Scenario		Method			
	Number of BS	3D	MUSIC-Based AOA Estimation	UCA	TDOA Estimation	EKF
[17]	2	✓	×	×	✓	×
[18]	8	✓	×	×	✓	×
[19]	3	✓	×	×	✓	×
[20]	5	✓	×	×	✓	×
[22]	2	✓	✓	✓	×	×
[23]	3	✓	×	×	✓	✓
[24]	4	×	×	×	✓	✓
[25]	2	✓	✓	×	×	✓
Our work	3	✓	✓	✓	✓	✓

1.2. Contributions

The main contributions of this paper are summarized as follows:

- This paper proposes an EKF-based hybrid AOA-TDOA localization method for UAVs in urban environments. The proposed framework operates as follows: measurements are first obtained independently using AOA and TDOA techniques. These measurements are then fused and processed using the EKF algorithm to achieve high-precision positioning. The RMSE is employed as the performance indicator to evaluate the positioning accuracy of the proposed algorithm.
- For AOA estimation, a UCA is utilized for array signal processing. The MUSIC algorithm is then applied to accurately estimate the signal's incident angle by leveraging the phase differences across the antenna elements. For TDOA-based estimation, to improve the accuracy of time difference measurement, a multipath signal separation and recognition function is adopted to effectively separate direct signals and multipath reflection signals by comprehensively analyzing the amplitude, phase, arrival time, and other characteristics of the received signal.
- Finally, the simulation results demonstrate that the proposed method outperforms conventional TDOA-only and AOA-only positioning schemes, achieving a positioning accuracy of approximately 5 m and an angular error of around 3° , which is suitable for applications in multipath environments such as urban areas.

1.3. Organizations and Notations

The rest of the paper is organized as follows. In Section 2, the system model and localization method are presented, and then a detailed explanation of localization methods based on AOA and TDOA is provided. Afterwards, a discussion on the data fusion of TDOA and AOA measurements using the EKF and a description of the proposed algorithm are provided in Section 3. To validate the effectiveness of the proposed method, in Section 4, simulation results and comparison experiments are carried out and assessed. Section 5 concludes the paper. Finally, a discussion of future work can be found in Section 6.

Notations: $(\cdot)^T$ and $(\cdot)^H$ indicate the transpose and conjugate transpose operation, respectively. $\|\cdot\|$ denotes the 2-norm. $\mathbb{E}[\cdot]$ denotes the expectation operator. $\exp(\cdot)$ is the exponential function, and $\otimes$ represents the Kronecker product. $\text{diag}[\cdot]$ represents the diagonal matrix.

2. Localization Based on AOA and TDOA

2.1. System Model and Localization Method

A single-input multiple-output (SIMO) wireless system is considered in this paper. It consists of three BSs and one UAV. An RF switch is used to connect all antenna elements to the receiver. Without loss of generality, the first BS is designated as the reference node. It is equipped with an M -element UCA with a radius of r . The antenna spacing d is set to half the carrier wavelength λ (i.e., $d = \frac{\lambda}{2}$). A three-dimensional Cartesian coordinate system is constructed to model the locations of BSs and the UAV, which can be denoted as $s_0 = [x_0, y_0, z_0]^T$, $s_1 = [x_1, y_1, z_1]^T$, $s_2 = [x_2, y_2, z_2]^T$, and $u = [x_u, y_u, z_u]^T$, respectively.

Figure 1 illustrates the block diagram of the proposed hybrid localization system. This approach leverages two complementary measurement principles. On one hand, the measurements of AOA are estimated by processing signals received at each element of the UCA using the MUSIC algorithm. On the other hand, the TDOA measurements between multiple BSs and the reference BS are measured to construct a set of hyperbolic equations for position estimation. To effectively fuse these heterogeneous and nonlinear AOA measurements, an EKF is employed for robust data fusion and accurate tracking of the UAV's position. Specifically, for TDOA-based positioning, signals from the UAV

are received by three BSs, yielding two independent TDOA measurements. Each TDOA defines a hyperboloid of possible locations. Their intersection typically results in a spatial curve. For AOA-based positioning, the reference BS, equipped with a UCA, estimates the signal's angle of arrival, characterized by the azimuth angle $\theta \in [0, 2\pi]$ and the elevation angle $\phi \in [0, \frac{\pi}{2}]$. This measurement constrains the UAV to lie along a specific direction.

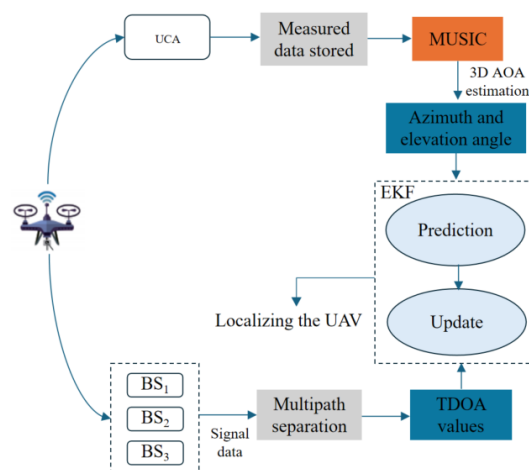


Figure 1. Block diagram of the localization process.

By combining the complementary information—AOA provides a directional constraint along the signal ray, while TDOA offers a relative range constraint defined by hyperbolic surfaces—the EKF provides a stable and accurate position estimate, effectively resolving the indeterminacy present when each measurement method is used in isolation.

2.2. AOA Measurements

The AOA estimation algorithm provides dual-dimensional angular measurements, comprising the azimuth angle to define the signal's horizontal bearing and the elevation angle to specify its vertical tilt relative to the receiver plane. For AOA-based positioning, this article employs a UCA for signal acquisition and applies the 3D MUSIC algorithm to process the received signals, enabling accurate estimation of the arrival angles of the target signal.

The signal received at the m -th antenna can be written as

$$\mathbf{X}(k) = \mathbf{A}\mathbf{S}(k) + \mathbf{N}(k) \quad (1)$$

where $\mathbf{X}(k) = [x_1(k), x_2(k), \dots, x_M(k)]^T$ denotes the array output vector; $\mathbf{S}(k) = [s_1(k), s_2(k), \dots, s_P(k)]^T$ is the source matrix; $\mathbf{N}(k) = [n_1(k), n_2(k), \dots, n_M(k)]^T$ is the received noise with $n_m(k) \sim (0, \sigma^2)$; $\mathbf{A} = [\mathbf{a}_1(\theta, \phi), \mathbf{a}_2(\theta, \phi), \dots, \mathbf{a}_P(\theta, \phi)]$ is the array flow pattern matrix, which depends on the incident angle of the signal source. $\mathbf{a}_p = \exp(-j2\pi\beta_m/\lambda)$, where β_m represents the wave path difference on the m -th element, which can be expressed as $\beta_m = r \cos\left(\frac{2\pi(m-1)}{M} - \theta\right) \cos(\phi)$.

Based on the array signal model, the array output covariance matrix can be calculated as

$$\begin{aligned} \mathbf{R}_X &= \mathbb{E}[\mathbf{X}(k)\mathbf{X}^H(k)] \\ &= \mathbf{A}\mathbf{R}_S\mathbf{A}^H + \sigma^2\mathbf{I} \end{aligned} \quad (2)$$

where $\mathbf{R}_S = \mathbb{E}[\mathbf{S}(k)\mathbf{S}^H(k)]$ is the source covariance matrix.

Then, we perform eigenvalue decomposition on the covariance matrix $\mathbf{R}_X$ to obtain bases for the beamspace signal and noise subspaces. Thus, the $\mathbf{R}_X$ can be rewritten as

$$\mathbf{R}_X = \mathbf{Q}\mathbf{\Sigma}\mathbf{Q}^H \quad (3)$$

where $\mathbf{\Sigma} = \text{diag}[\lambda_1, \lambda_2, \dots, \lambda_M]$.

According to [26], the eigenvalues of the signal subspace are consistently larger than those of the noise subspace. Based on this distinction, the two subspaces can be separated by sorting the eigenvalues as follows

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p \geq \lambda_{p+1} = \dots \lambda_M = \sigma^2 \quad (4)$$

where $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p$ are related to the signal, so they compose the signal subspace, while the remaining $M - p$ eigenvalues are entirely dependent on noise, and their corresponding eigenvectors form the noise subspace. Let $\mathbf{\Lambda}_s$ and $\mathbf{\Lambda}_n$ denote the signal subspaces and noise subspaces orthonormal matrices. They can be expressed as

$$\mathbf{\Lambda}_s = [e_1, e_2, \dots, e_p], \mathbf{\Lambda}_n = [e_{p+1}, e_{D+2}, \dots, e_M] \quad (5)$$

Based on the orthogonality of the steering vector and the noise subspace [27], we can obtain the MUSIC spectrum as

$$P_{\text{MUSIC}}(\theta, \phi) = \frac{1}{\|\mathbf{\Lambda}_n^H \mathbf{a}_p(\theta, \phi)\|} = \frac{1}{\mathbf{a}_p^H(\theta, \phi) \mathbf{\Lambda}_n \mathbf{\Lambda}_n^H \mathbf{a}_p(\theta, \phi)} \quad (6)$$

The peak of the spatial spectrum corresponds to the signal's direction of arrival. Therefore, the azimuth and elevation angles in 3D space can be estimated by finding the roots of the polynomial equation.

$$(\theta, \phi) = \arg \max(P_{\text{MUSIC}}(\theta, \phi)) \quad (7)$$

2.3. TDOA Measurements

In the TDOA-based positioning method, signals transmitted from the UAV are received by multiple base stations. A minimum of three and four base stations are required for 2D and 3D positioning, respectively. While capable of delivering high localization accuracy in practice, TDOA technology is susceptible to challenges like multipath interference. The superposition of signals alters their time of arrival, which prevents the algorithm from accurately estimating the time difference, thereby adversely affecting the positioning accuracy. To address this, we utilize matched filter and peak detection to separate the direct signal and suppress multipath effects, greatly enhancing the precision of time-difference estimation [28].

Assuming that the total received signal is composed of a direct signal and multiple multipath signals, it can be modeled as

$$r_i(k) = s(k) + \sum_{l=1}^L \alpha_l s(k - \tau_l) + n_i(k), i = 0, 1, 2. \quad (8)$$

where $s(k) = \exp(-k^2/2\sigma^2)$ is the transmitted signal, L denotes the number of multipath components, α_l denote the attenuation factor of signal strength, τ_l represents the time delay between the l -th path and transmit signal, respectively, and $n_i(k)$ represents the zero-mean additive Gaussian noise.

The correlation function method is a time delay estimation technique based on signal correlation. It determines the time delay by computing the correlation level between a signal and itself or a known template signal. Therefore, the cross-correlation function between receive signal and direct signal can be expressed as

$$R_i(\tau) = \int_{-\infty}^{+\infty} r_i(k)s^*(k-\tau)dk \quad (9)$$

Remark 1. When $\tau = 0$, $R_i(\tau)$ attains its maximum value, which occurs when the signals are perfectly coincident. Therefore, the time delay can be estimated by identifying the τ that corresponds to the maximum value of $R_i(\tau)$.

Subsequently, we detect the peaks P_0 and identify the direct path τ_i^{direct} based on their temporal positions and amplitudes.

$$\begin{aligned} P_0 &= \{\tau_j | R_i(\tau_j) > T\}, j = 1, \dots, M. \\ \tau_i^{\text{direct}} &= \arg\max(\tau_j \in P_0) \end{aligned} \quad (10)$$

where T is a threshold.

Let d_i denote the Euclidean distance between the source and BSs, which can be expressed as

$$d_i = \|u - s_i\| = \sqrt{(u - s_i)^T(u - s_i)}, i = 0, 1, 2. \quad (11)$$

Then, all TDOA measurements can be obtained based on (10).

$$d_{i0} = d_i - d_0 = c * \Delta\tau_{i0}, i = 1, 2. \quad (12)$$

where d_{i0} is the range difference, $\Delta\tau_{i0} = \tau_i^{\text{direct}} - \tau_0^{\text{direct}}$ denotes the time difference of arrival, and c is the speed of light.

3. Data Fusion of AOA and TDOA Measurements via EKF

Building upon the individual principles of AOA and TDOA positioning presented in Section 2, this section develops the hybrid localization framework. We employ an EKF to fuse the AOA and TDOA measurements based on the system's state-space and observation models, leveraging their complementary characteristics to enhance the estimation accuracy and robustness of the UAV's positioning.

According to the kinematic model, the state transition equation of UAV can be expressed as

$$u(k/k-1) = u(k-1) + \Delta t v(k-1) \quad (13)$$

where Δt is the time interval. $v = [v_x, v_y, v_z]^T$ is the UAV velocity in each direction.

The Kalman filter provides a recursive process for real-time state estimation. Initialized with a state vector and an error covariance matrix, it iteratively updates the state estimate at each time step by incorporating new measurement data. The iterative procedure is described in detail as follows:

(1) Prediction step:

First, the state prediction equation and the covariance matrix of prediction error are respectively given by

$$s(k/k-1) = G(k-1)s(k-1) + B(k-1)a(k-1) \quad (14)$$

$$P(k/k-1) = G(k-1)P(k-1)G^T(k-1) + Q(k-1) \quad (15)$$

where $s(k) = [x_u, y_u, z_u, v_x, v_y, v_z]^T$ represents the state vector at the k -th moment and $a(k-1)$ denotes the current state of control, which is set to 0 and will not be discussed in detail here. $Q(k)$ represents the process noise covariance matrix, which reflects the intensity of system fluctuations between consecutive time steps. A smaller value of $Q(k)$ corresponds to a higher degree of confidence in the dynamic model, which in turn facilitates faster convergence of the system.

$$G(k) = I_3 \otimes \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad (16)$$

is the state transition matrix, I_3 denotes the 3×3 identity matrix.

$$B(k) = I_3 \otimes \begin{bmatrix} \frac{\Delta t^2}{2} & \Delta t \end{bmatrix}^T \quad (17)$$

is the control matrix.

(2) *Correction step:*

The Kalman gain $K(k)$ can be calculated as

$$K(k) = P(k/k-1)H^T(k) \times \left(H(k)P(k/k-1)H^T(k) + R(k) \right)^{-1} \quad (18)$$

where $R(k)$ is the measurement noise covariance matrix. $H(k)$ denotes the observation transition matrix, which can be calculated by applying the partial derivatives [25,29]. The elements of $H(k)$ can be represented as

$$H(k) = \begin{bmatrix} \frac{\partial d_{10}}{\partial x} & \frac{\partial d_{10}}{\partial y} & \frac{\partial d_{10}}{\partial z} & 0 & 0 & 0 \\ \frac{\partial d_{20}}{\partial x} & \frac{\partial d_{20}}{\partial y} & \frac{\partial d_{20}}{\partial z} & 0 & 0 & 0 \\ \frac{\partial \theta}{\partial x} & \frac{\partial \theta}{\partial y} & 0 & 0 & 0 & 0 \\ \frac{\partial \phi}{\partial x} & \frac{\partial \phi}{\partial y} & \frac{\partial \phi}{\partial z} & 0 & 0 & 0 \end{bmatrix} \quad (19)$$

where the elements of observation matrix $H(k)$ for the AOA estimation are calculated as

$$\begin{aligned} \frac{\partial \theta}{\partial x_u} &= -\frac{y_u - y_0}{r_h^2} \\ \frac{\partial \theta}{\partial y_u} &= \frac{x_u - x_0}{r_h^2} \\ \frac{\partial \theta}{\partial z_u} &= 0 \\ \frac{\partial \phi}{\partial x_u} &= -\frac{(x_u - x_0)(z_u - z_0)}{r_h d_i^2} \\ \frac{\partial \phi}{\partial y_u} &= -\frac{(y_u - y_0)(z_u - z_0)}{r_h d_i^2} \\ \frac{\partial \phi}{\partial z_u} &= \frac{r_h}{d_0^2} \\ r_h &= \sqrt{(x_u - x_0)^2 + (y_u - y_0)^2}. \end{aligned} \quad (20)$$

The elements of observation matrix $H(k)$ for TDOA estimation are computed as

$$\begin{aligned}
\frac{\partial d_{i0}}{\partial x_u} &= \left(\frac{x_u - x_i}{d_i} - \frac{x_u - x_0}{d_0} \right) \\
\frac{\partial d_{i0}}{\partial y_u} &= \left(\frac{y_u - y_i}{d_i} - \frac{y_u - y_0}{d_0} \right) \\
\frac{\partial d_{i0}}{\partial z_u} &= \left(\frac{z_u - z_i}{d_i} - \frac{z_u - z_0}{d_0} \right), i = 1, 2.
\end{aligned} \tag{21}$$

(3) *Updated step:*

The state vector is estimated by updating the predicted state given in (14) using the Kalman gain and new measurement, which can be expressed as

$$\hat{\mathbf{s}}(k/k) = \hat{\mathbf{s}}(k/k-1) + \mathbf{K}(k)(\mathbf{z}(k) - \hat{\mathbf{z}}(k)) \tag{22}$$

where $\mathbf{z}(k) = \mathbf{H}(k)\mathbf{s}(k) + \mathbf{v}(k)$ represents the measured value at time k , and $\hat{\mathbf{z}}(k) = \mathbf{H}(k)\hat{\mathbf{s}}(k/k-1)$ is the prediction value at time k . $\mathbf{v}(k)$ represents the measurement noise.

Finally, the covariance matrix is updated as follows

$$\mathbf{P}(k/k) = [\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k)]\mathbf{P}(k/k-1) \tag{23}$$

Substituting (22) and (23) into (14) and (15), respectively, we iterate this process for all measurement snapshots. The EKF-based hybrid AOA-TDOA localization algorithm is described in Algorithm 1.

Algorithm 1 EKF-based hybrid AOA-TDOA localization algorithm.

- 1: **Input:** $M, L, c, f_c, \Delta t, s_i, u, O$;
 - 2: **Output:** $\hat{\mathbf{u}}$
 - 3: Set the maximum iteration number K_{max} and $k = 1$.
 - 4: **Initialization:** Kalman filter states $\mathbf{s}(k)$ and covariance matrix $\mathbf{P}(k)$;
 - 5: Define process noise and measurement noise covariance matrix $\mathbf{Q}(k)$ and $\mathbf{R}(k)$;
 - 6: **While** $k < K_{max}$ **do**
 - 7: **Stage 1:** AOA measurement
 - 8: **repeat**
 - 9: Construct steering vector $\mathbf{a}_p(\theta, \phi)$;
 - 10: Compute the covariance matrix $\mathbf{R}_X$;
 - 11: Perform eigenvalue decomposition;
 - 12: Compute MUSIC spectrum $P_{MUSIC}(\theta, \phi)$ according to Equation (6);
 - 13: Peak search to estimate (θ, ϕ) ;
 - 14: **Stage 2:** TDOA measurement
 - 15: Calculate the cross-correlation function $R_i(\tau)$;
 - 16: Peak detection and identifying the direct path using Equation (10).
 - 17: Calculate true distance between UAV and BSs;
 - 18: Generate TDOA measurements using Equation (12);
 - 19: **Stage 3** Extended Kalman filter prediction and update
 - 20: State prediction $\mathbf{s}(k)$ using Equation (14);
 - 21: Covariance prediction $\mathbf{P}(k/k-1)$ using Equation (15);
 - 22: Kalman gain computation $\mathbf{K}(k)$ using Equation (18);
 - 23: State update $\hat{\mathbf{s}}(k/k)$ using Equation (22);
 - 24: Covariance update $\mathbf{P}(k/k)$ using Equation (23);
 - 25: $k = k + 1$
 - 26: **End While**
-

4. Simulation and Discussion

In this section, some experiments are designed to evaluate the proposed EKF-based hybrid AOA-TDOA positioning method, with two benchmark algorithms selected for comparison.

4.1. Simulation Setup

The simulation is conducted according to the following procedure, which simulates a complete processing chain. Specifically, raw multipath-corrupted signals are first generated according to geometric and channel settings. Then, TDOA measurements are extracted using the proposed multipath separation function. Meanwhile, AOA measurements are obtained via the UCA-MUSIC algorithm. The resulting measurements, which inherently contain algorithm-induced errors (e.g., standard deviations), are fed into the EKF for fusion and tracking. Finally, the localization performance (e.g., root mean square error) reported in the results are derived from Monte Carlo simulation by comparing the final estimated position with the truth values.

Without loss of generality, the locations of the three BSs are set to $s_0 = [0, 0, 30]^T$ m, $s_1 = [200, 0, 50]^T$ m and $s_2 = [0, 200, 60]^T$ m, respectively. The UAV's initial position is $[100, 100, 30]^T$ m, and its initial motion state vector, i.e., $[x_u, y_u, z_u, v_x, v_y, v_z]^T$, is set to $[100, 100, 30, 3, 2, 0.5]^T$. For the filter initialization, the process and error covariances matrix are set to $Q = \text{diag}([0.01 \ 0.01 \ 0.01 \ 0.01 \ 0.01 \ 0.01])$ and $P = \text{diag}([5 \ 5 \ 5 \ 0.5 \ 0.5 \ 0.5])$, respectively. The measurement noise covariance matrix is set to $R = \text{diag}[\sigma_{TDOA}^2 \ \sigma_{TDOA}^2 \ \sigma_{AOA}^2 \ \sigma_{AOA}^2]$. Moreover, the angular search step is set to 0.5° for the MUSIC-based AOA estimation. The threshold T , determined based on signal detection theory, is set to 3.5σ . Unless otherwise specified, the detailed simulation parameters are listed in Table 2.

Table 2. Simulation parameters.

Parameter Name	Parameter Value
Sampling frequency f_c	2.4 GHz
Sampling interval Δt	0.1 s
Number of BSs N	3
Signal and noise ratio SNR	20 dB
Speed of light c	3×10^8 m/s
Snapshots O	100
Number of UCA's array elements M	8
The antenna spacing of UCA d	$\frac{1}{16}$ m
Number of multipath components L	2
Attenuation factor of signal strength α_l	0.3
Time delay of the l -th path τ_l	1 μ s
The standard deviation of AOA estimation σ_{AOA}	1 degree
The standard deviations of TDOA estimation σ_{TDOA}	10 ns

The RMSE criterion is used to measure the difference between the true and estimated UAV's position. It is defined as

$$\text{RMSE}(u) = \sqrt{\frac{1}{J} \sum_{j=1}^J \|u - \hat{u}\|^2} \quad (24)$$

where u denotes the true position of the UAV, $\hat{u}$ is the estimated position.

Moreover, to demonstrate the performance advantages of the proposed algorithm, we compare it with the following two benchmark schemes:

- (1) *The Baseline 1 (AOA-based Method)*: Under this scheme, array signal processing is performed using three independent UCA arrays in conjunction with the MUSIC algorithm to estimate AOA. The estimated AOAs are subsequently processed by an EKF to track the position of the UAV.
- (2) *The Baseline 2 (TDOA-based Method)*: Under this scheme, a multipath signal separation function is employed to effectively isolate the direct signal from multipath reflections. The resulting TDOA measurements are subsequently processed using an EKF to track the UAV's position. Adhering to the four-base-station requirement for 3D TDOA, the baseline TDOA-only scheme is configured with the original three base stations plus an additional one at $s_3 = [200, 200, 40]^T$. This configuration features no UCA installations on any base station.

A detailed comparison between the proposed hybrid positioning and two benchmark schemes is provided in Table 3.

Table 3. Comparison of the proposed scheme with benchmark schemes.

Scheme	Number of BSs	Number of UCAs	Number of Measurements	Hardware Cost	Time Sync. Requirements
Hybrid AOA-TDOA	3	1	4	medium	medium
TDOA-only	4	0	3	low	high
AOA-only	3	3	6	high	low

4.2. Simulation Results

In this subsection, the performance of the proposed algorithms is evaluated in terms of RMSE via MATLAB R2021a simulation. The results are compared with those obtained using methods that are solely reliant on TDOA or AOA positioning. A comparison between the UAV's true position and its estimated position in all directions at $k = 10$ s is provided in Table 4.

Table 4. Target observed and estimated positions.

Target/Coordinates	Observed (m)	Estimated (m)
X	130 m	133 m
Y	120 m	124 m
Z	35 m	38 m

Figure 2 illustrates the UAV's position estimated by the EKF in each spatial dimension. It can be observed that the estimation accuracy consistently improves over time in the X-axis and Y-axis directions. This is because as time progresses, the filter accumulates more measurements, which gradually reduces the estimation uncertainty, thereby demonstrating the effectiveness of the proposed method. This phenomenon is primarily caused by a well-distributed geometry of base stations in the horizontal plane, coupled with limited diversity in the vertical direction. Larger errors are observed in the Z-axis direction because the horizontal position can be mutually corrected by TDOA measurements. In contrast, the height information relies primarily on angle measurements, which are more susceptible to noise and geometric dilution.

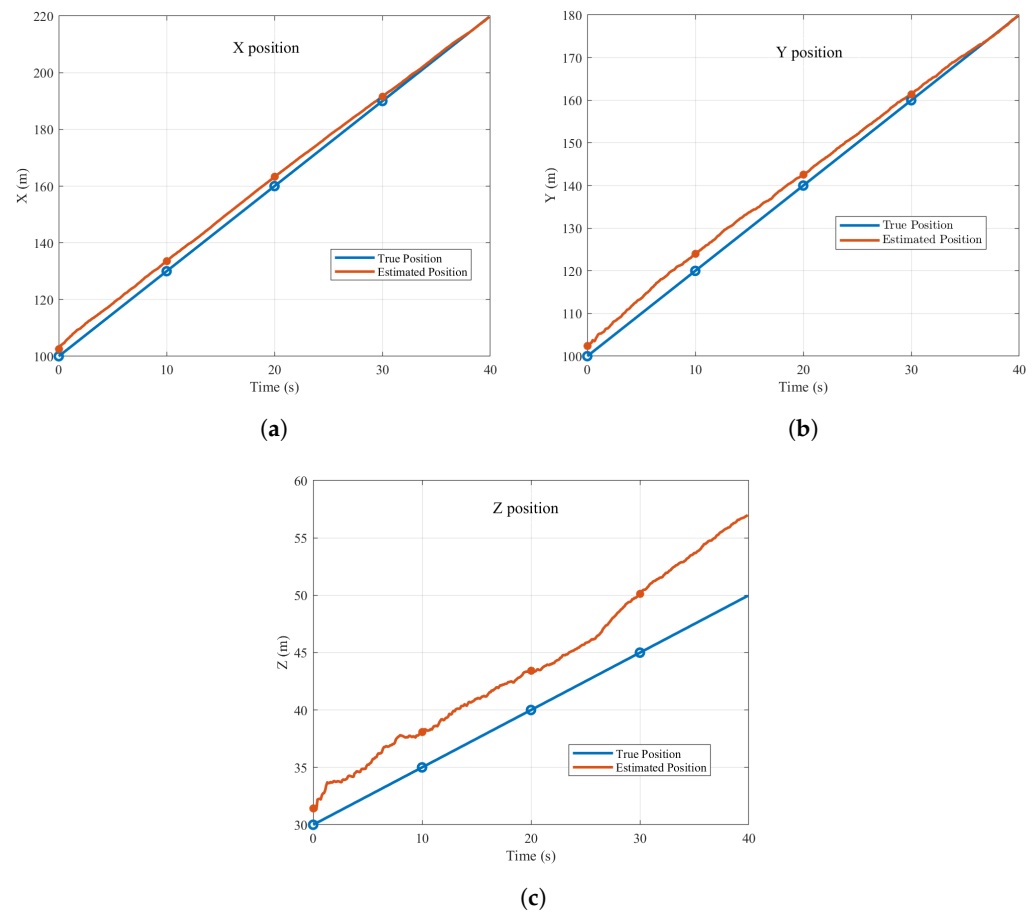


Figure 2. (a) UAV position estimated for X direction versus time. (b) UAV position estimated for Y direction versus time. (c) UAV position estimated for Z direction versus time.

To analyze the relationship between the number of array elements M in the UCA and the positioning performance, Figure 3 plots the RMSE and angle error curves versus M , with the number of snapshots fixed at 500. As shown in Figure 3, the RMSE decreases as M increases. This is because a larger array of elements provides higher angular resolution, which in turn reduces the AOA estimation error. Additionally, it can be seen that the RMSE rises as the angular search step increases. This demonstrates that a finer search step yields higher positioning accuracy.

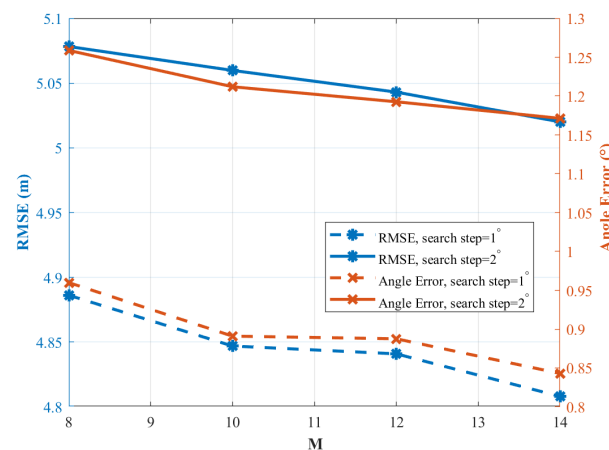


Figure 3. RMSE curves versus the number of the UCA's array elements.

Figure 4 depicts the AOA estimation results of the proposed method. From Figure 4a,b, it can be observed that the estimated azimuth and elevation angles approach the actual values over time. Furthermore, as shown in Figure 4c, the MUSIC algorithm achieves an angular estimation error of approximately 3° and exhibits stable performance over time. This indicates that the proposed MUSIC algorithm can effectively estimate the direction of the target.

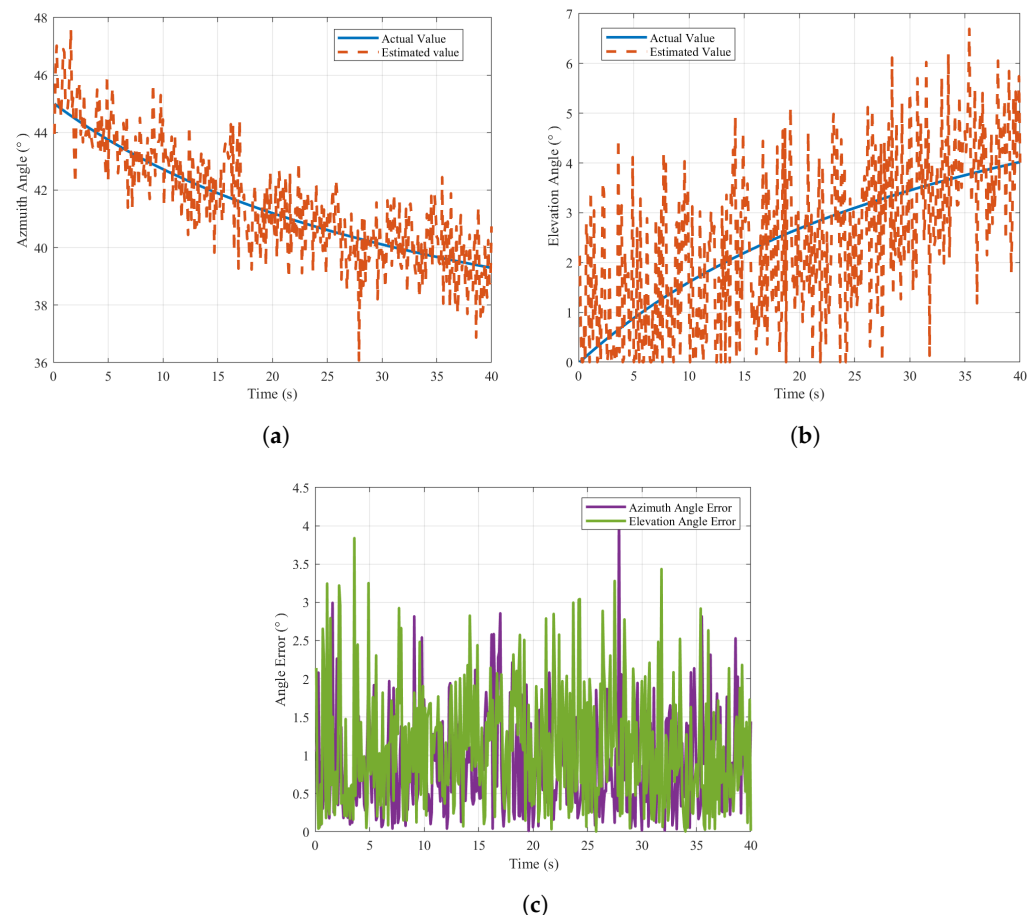


Figure 4. (a) Comparison between true and estimated azimuth values. (b) Comparison between true and estimated elevation values. (c) Angle estimation error.

Figure 5 shows the RMSE performance versus the number of multipath components, i.e., L , which varies from 2 to 5. It can be observed that the proposed hybrid positioning method is largely unaffected by multipath components when the SNR is 10 dB or higher, demonstrating its robustness against multipath effects and suitability for multipath environments such as urban areas. However, in the low-SNR region, the RMSE increases rapidly with L , especially for $L > 3$. This indicates that multipath components significantly degrade the positioning accuracy under low-SNR conditions.

Figure 6a,b present the RMSE values of different positioning methods versus the standard deviation of AOA measurement noise σ_{AOA} and the standard deviation of TDOA measurement noise σ_{TDOA} . It is clear that the proposed hybrid method outperforms the pure AOA-EKF and TDOA-EKF methods. Moreover, it can be seen that the RMSE values of both the proposed and the AOA-EKF methods increase with σ_{AOA} , indicating that AOA measurement noise degrades positioning accuracy. Furthermore, we observe that the AOA-EKF method exhibits greater sensitivity to this noise. This is because the pure AOA positioning approach relies solely on angle information, whose positioning error increases with distance. Unlike AOA, the proposed hybrid method leverages the distance

information provided by TDOA, which helps constrain and compensate for deviations in the AOA measurements. Similar to the trend shown in Figure 6a, the RMSE of the proposed hybrid method increases gradually, whereas that of the pure TDOA-EKF method grows significantly, particularly beyond 40 ns. This is because that the pure TDOA-EKF method relies exclusively on time differences of signal arrival between different base stations, making it more vulnerable to TDOA measurement noise. Analytical results demonstrate that the proposed hybrid positioning method achieves an accuracy improvement of approximately 42% compared to the pure TDOA-EKF method.

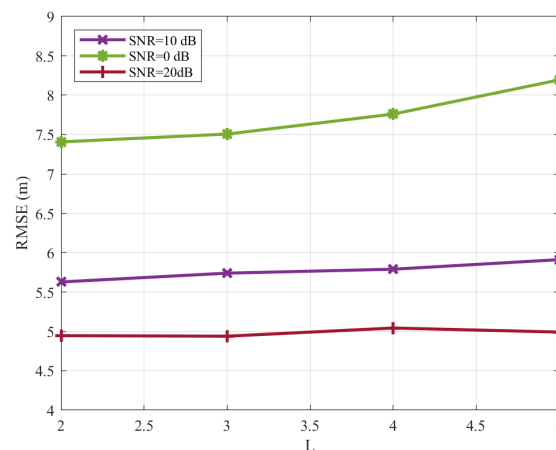


Figure 5. RMSE curves versus the number of the multipath components.

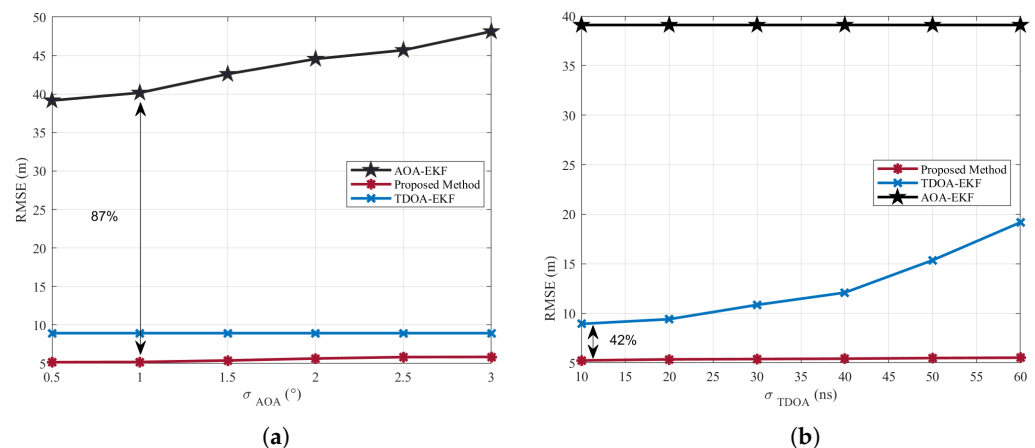


Figure 6. (a) RMSE of the different positioning methods with different σ_{AOA} . (b) RMSE of the different positioning methods with different σ_{TDOA} .

Figure 7 illustrates the RMSE performance under different SNRs and noise standard deviations. From Figure 7, it can be seen that the performance gaps among the three noise levels diminish with increasing SNR, indicating that a higher SNR can effectively compensate for noise-induced degradation. Specifically, at an SNR level of 10 dB, the proposed method achieves RMSE values of 6.35 m, 6.03 m and 5.87 m under the three noise levels, respectively. Moreover, it can be observed that an angular error exerts a greater influence on positioning accuracy than a time synchronization error.

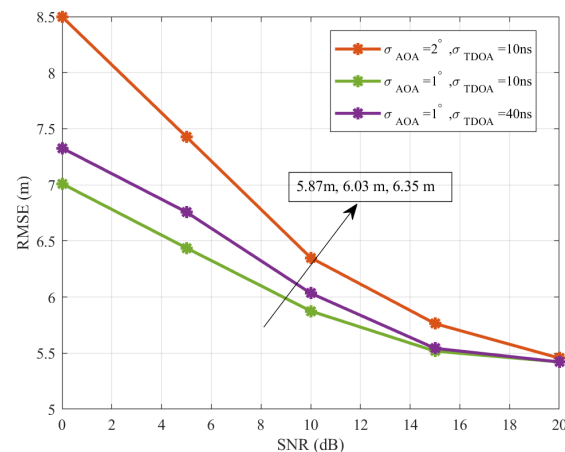


Figure 7. RMSE at different SNRs and noise levels.

5. Conclusions

This paper proposes an EKF-based hybrid positioning approach that fuses AOA and TDOA for UAV localization in urban scenarios. Specifically, the MUSIC algorithm with a UCA is employed for accurate AOA. For TDOA-based positioning, a multipath signal separation function is employed to effectively isolate the direct signal from its multipath reflections, thereby improving the accuracy of time-difference estimation. The TDOA measurements are then derived from the time delay of the direct path. Finally, these AOA and TDOA measurements are fused within an EKF framework. The state transition matrix in the EKF is designed to capture the dynamic evolution of the UAV through its parameter update mechanism, enabling consistent tracking. The simulation results demonstrate that the proposed method achieves a positioning accuracy of approximately 5 m and an angular error within 3° , outperforming several baseline methods. In summary, this work presents a comprehensive and effective solution for UAV positioning in urban environments.

6. Future Work

While this work has validated the fundamental effectiveness of the proposed EKF-based hybrid TDOA-AOA positioning method, several important aspects must be explored in future research to enhance its robustness and practicality. First, a quantitative analysis is necessary to systematically assess the impact of peak misdetection probability and rank loss in multipath environments on positioning accuracy. Second, enhancing the algorithm's robustness in challenging NLOS scenarios—specifically those where a strong multipath component obscures or dominates the direct path—will be crucial for real-world deployment. Finally, a comprehensive comparative evaluation with other advanced hybrid algorithms, such as hybrid Weighted Least Squares and Iteratively Reweighted Recursive Least Squares methods, will be conducted to further benchmark the performance and relative advantages of the proposed framework.

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Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned Aerial Vehicle.
SIMO	Single-Input Multiple-Output.
TDOA	Time Difference of Arrival.
AOA	Angle of Arrival.
3D	Three-Dimensional.
EKF	Extended Kalman Filter.
RF	Radio Frequency.
UCA	Uniform Circular Array.
MUSIC	Multiple-Signal Classification.
ESPRIT	Estimation of Signal Parameters via Rotational Invariance Techniques.
LOS	Line-of-Sight.
SNR	Signal-to-Noise Ratio.
RMSE	Root Mean Squared Error.

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