

High-Precision and Low-Complexity ToA Estimation for Sensor Networks in GNSS-Denied Scenarios via Waveform–Algorithm Co-Design

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High-Precision and Low-Complexity ToA Estimation for Sensor Networks in GNSS-Denied Scenarios via Waveform–Algorithm Co-Design

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Abstract— In disaster zones or infrastructure-less areas, Global Navigation Satellite Systems (GNSS) are vulnerable to jamming and spoofing attacks, often leading to signal denial. Radio positioning serves as a critical backup for high-precision spatiotemporal reference measurement, particularly for wireless sensor networks (WSNs) operating in GNSS-denied environments. However, long-range radio signal propagation faces challenges such as extreme path loss, severe multipath effects, and insufficient chip-level delay resolution. These factors make Time-of-Arrival (ToA) estimation extremely difficult, limiting pseudorange accuracy and consequently constraining overall navigation performance. To address this, we propose a System-Aware Time-of-Arrival (SA-ToA) method that synergistically integrates waveform design and algorithm processing. First, we define a four-dimensional orthogonal spread spectrum signal architecture (Time-Frequency-CDMA-Time Hopping, T-F-CDMA-TH), which provides the necessary prior knowledge for sensor node acquisition. Subsequently, we design a three-stage collaborative mechanism comprising scheduling-guided coarse acquisition, an improved CLEAN-based multipath separation, and parabolic fitting-based sub-sample fine estimation. This approach optimizes ranging performance in complex environments. Theoretically, we derive that under ideal single-path conditions with a 40 MHz bandwidth and a 16 dB despread Signal-to-Noise Ratio (SNR), the Cramér-Rao Lower Bound (CRLB) for ToA estimation is 0.46 meters. Monte Carlo simulations validate the robustness of the SA-ToA method against typical disturbances, including fractional sampling delays, timing jitter, and strong multipath interference. Results show that under Line-of-Sight (LoS) conditions, the Root Mean Square (RMS) ranging error is better than 1.65 m for short ranges (10–100 m) and better than 5 m for long ranges (200 km). Even under severe near-end multipath interference (NLoS1/NLoS2) and low-SNR conditions (down to 0 dB), the proposed method achieves robust numerical convergence with 100 % availability across all Monte-Carlo test runs. Comparative analysis with classical estimation methods demonstrates that the SA-ToA method reduces the RMS error by an order of magnitude, approaching the theoretical limit most closely. Thus, the proposed method holds significant potential for enhancing radio positioning system performance in GNSS-denied scenarios.

Index Terms— Time-of-arrival estimation, spread-spectrum communication, waveform-algorithm co-design, CLEAN algorithm, multipath mitigation, signal processing.

I. INTRODUCTION

Global Navigation Satellite Systems (GNSS) are critical for civil infrastructure applications such as emergency response and disaster management. Nevertheless, natural disasters, atmospheric disturbances, and intentional jamming can disrupt GNSS signals and break Positioning, Navigation, and Timing (PNT) services [1]. For post-disaster missions, unmanned aerial vehicles (UAVs) and ground robots require continuous positioning capability, but GNSS frequently becomes unavailable inside collapsed buildings or underground environments [2]. Consequently, GNSS-independent backup positioning solutions are highly demanded.

Radio positioning, characterized by its independence from external infrastructure and good anti-jamming capability, is regarded as a reliable backup for building PNT capabilities in GNSS-denied environments. By measuring Time-of-Arrival (ToA) of signals from ground stations, pseudorange observations are obtained to determine receiver positions [3]. In many practical scenarios, such as disaster response or battlefield surveillance, positioning is performed by resource-constrained sensor nodes with limited battery and computational power. Hence, ToA estimation accuracy is decisive for the precision and reliability of radio positioning systems.

Current research focuses on improving long-range ranging architectures, utilizing external sources, and enhancing ToA estimation algorithms. Kim et al. optimized eLoran-transmitted pulses; however, its narrow effective bandwidth (< 1 kHz) fundamentally prevents meter-level ranging accuracy [4]. Yang et al. proposed a carrier-phase ranging scheme, whose performance degrades under dynamic platform conditions [5]. Zhao et al. constructed a propagation-delay prediction model that suffers from limited generalization across diverse operational scenarios [6]. Kassas et al. demonstrated positioning feasibility using Starlink signals, yet this approach relies on high-gain phased-array hardware [7]. While Zeng et al. investigated LEO-constellation synchronization mechanisms, their work leaves ToA acquisition under weak-signal conditions unresolved [8]. Shang et al. deployed the MEDLL algorithm within inertial-navigation frameworks; nevertheless, their solution still requires GNSS aiding and cannot operate in fully GNSS-denied settings [9]. Hu et al. combined deep-learning modules with GNSS positioning, though the resulting multimodal model exhibits low physical interpretability [10]. Li et al. adopted reconfigurable intelligent surfaces (RIS) to reconstruct virtual Line-of-Sight paths, which imposes stringent hardware requirements for practical deployment [11]. Ji and Wu developed the MSIT scheme for high-frequency (HF) sensor networks; nevertheless, porting MUSIC-type super-resolution processing to UHF receivers yields substantial embedded computational overhead [12]. Song et al. put forward an eLoran differential-correction algorithm, which is heavily dependent on external real-world environmental datasets [13].

Beyond these, several state-of-the-art (SOTA) approaches have recently emerged, including deep-learning/Transformer-based methods (e.g., PE-MSRN [14], UWB TDoA Transformer [15]), subspace/super-resolution methods (MUSIC [16]), and interference-robust statistical detection (GLRT [17]). Nevertheless, all these methods follow the fixed-waveform, receiver-only

optimization paradigm. They treat transmit waveforms as predefined inputs and only optimize receiver processing. As a result, the performance potential brought by waveform-algorithm co-design remains largely unexplored.

To overcome this limitation, this paper presents the System-Aware Time-of-Arrival (SA-ToA) method for joint waveform design and algorithm processing. At the waveform layer, we define the four-dimensional orthogonal spread-spectrum architecture T-F-CDMA-TH (Time Slot-Frequency-CDMA-Time Hopping). System-level prior knowledge including static time-slot assignments and hopping sequences is embedded within the waveform. This supplies deterministic search priors and compresses the signal acquisition window from the full 15 ms frame down to 310 μ s. In addition, the built-in 125 μ s guard interval creates a clean noise-estimation region with no extra communication overhead. Building on this waveform foundation, we design a three-stage collaborative estimation algorithm: (1) scheduling-guided coarse acquisition, (2) improved SNR-adaptive soft-threshold CLEAN [18] multipath separation, and (3) sub-sample fine estimation via three-point parabolic fitting. Using systematic Monte-Carlo simulations, we show that SA-ToA reduces RMS ranging error by one order of magnitude relative to classical approaches. It maintains 100 % estimation availability under severe multipath at SNR as low as 0 dB and exhibits robustness for Doppler shifts up to 500 m/s. An FPGA resource and latency estimation (< 1 ms) is provided to assess the computational feasibility of the proposed method on representative embedded platforms, laying a foundation for future hardware prototyping.

II. RANGING SENSOR MODEL AND SYSTEM ARCHITECTURE

A. Design of System-Aware Sensor Architecture

To achieve high-precision ranging for broadcast radio positioning systems in GNSS-denied environments, this paper combines the integrated sensing and communication (ISAC) paradigm [19,20] and designs a four-dimensional orthogonal spread spectrum waveform scheme, termed T-F-CDMA-TH, tailored for the unified requirements of high precision and high stability over both short and long distances. This scheme achieves orthogonal resource allocation across the four dimensions of time, frequency, code division, and time hopping, while embedding system scheduling information (primary slot assignment, frequency hopping sequence, spreading code) directly into the waveform structure. The receiver can leverage this deterministic prior knowledge to reduce signal acquisition complexity and enhance multipath mitigation capability. The above four-dimensional resources are highly complementary: the time and frequency dimensions construct the coarse-grained resource grid of the system, code division multiple access enables code-domain user separation, and the time hopping dimension provides the structural redundancy required for noise estimation and collision mitigation. The T-F-CDMA-TH scheme is specifically defined as follows.

(1) Time slot dimension (T): Coarse-grained multiple-access isolation among ground stations is achieved through the time slot dimension. Without this dimension, signals from different stations would collide in the time domain at the receiver. The system frame length is set to 15 ms, divided into 4 primary time slots, each of length 3.75 ms, forming a coarse-grained frame structure.

Each ground station is statically assigned a unique primary slot index, achieving basic isolation among stations through the time-division multiple access mechanism to avoid mutual signal interference.

(2) Time hopping dimension (TH): To further increase multi-user capacity and reduce collision probability, each primary slot is further subdivided into 10 sub-slots, constructing a fine-grained sparse transmission and noise observation window. A spread-spectrum signal of duration $250\ \mu\text{s}$ is transmitted at the start of a designated hopping sub-slot, followed by a guard interval of $125\ \mu\text{s}$. No valid signal is transmitted within this guard interval. The received samples over this interval represent pure noise and enable high-precision noise-power estimation for subsequent algorithm modules.

(3) Code division dimension (CDMA): The system supports 4095-chip Gold codes and 127-chip repeated Zadoff-Chu spreading codes, with a chip rate of 32 Mcps, providing a processing gain of 36.1 dB. Through the code division mechanism, even when different ground stations transmit in the same sub-slot, they can be separated by assigning different spreading codes. Code division multiple access ensures that the system capacity is no longer limited by the finite number of time slots and hopping sequences, guaranteeing scalability for large-scale node deployment.

(4) Frequency dimension (F): The 40 MHz system bandwidth determines the fundamental ranging resolution and directly constrains the achievable Cramér-Rao Lower Bound (CRLB). A narrower bandwidth would fail to meet the meter-level theoretical ranging accuracy requirement, while a wider bandwidth would incur increased hardware complexity without commensurate performance gain under the target SNR conditions. The system operates with a fixed center frequency of 2.42 GHz and a bandwidth of 40 MHz. This frequency band is license-free, facilitating rapid deployment. During system operation, all ground stations and receivers operate uniformly within this band, ensuring consistency of frequency domain resources.

As shown in Fig. 1, a hopping pre-assignment sequence [1, 4, 6, 9] is used as an example to illustrate the four-dimensional orthogonal spread spectrum waveform scheme. The ground station transmits pulses only in sub-slots indexed 1, 4, 6, 9 of each frame, achieving a 40% duty cycle, while remaining silent in the other sub-slots. In practical deployment, mutually orthogonal hopping sequences can be assigned to different ground stations; as long as stations do not occupy the same sub-slot within the same frame, collision-free multi-user access can be realized. Furthermore, code division multiple access can be combined to further increase system capacity.

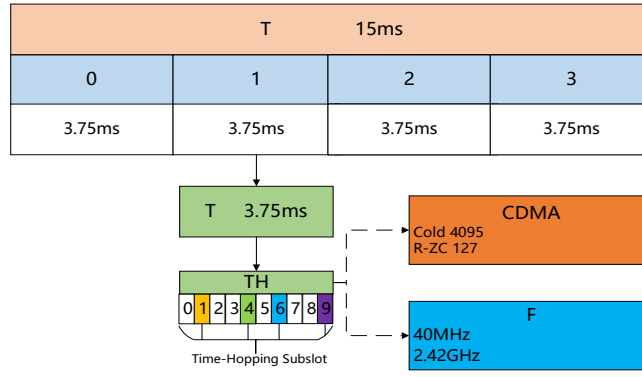


Fig.1. T-F-CDMA-TH System-Aware Framework.

B. Channel Model and Ranging Performance Requirements

The receiver of the radio positioning system passively receives the spread-spectrum signals transmitted by ground stations. During long-distance propagation, these signals are reflected by obstacles such as buildings and water surfaces, introducing Non-Line-of-Sight (NLoS) propagation path errors, which in turn affect the accuracy of the receiver's TOA estimation. In this paper, a multipath channel model is adopted to define the baseband received signal, and the signal model is given by Eq. (1):

$$r(t) = \sum_{l=0}^{L-1} \alpha_l s_m(t-\tau_l) + n(t) \quad (1)$$

where $s_m(t)$ represents the signal transmitted by the m -th ground station; $\tau_0 < \tau_1 < \dots < \tau_{L-1}$ denote the delays of the various propagation paths; L is the total number of multipath components; $\alpha_l \in \mathbb{C}$ represents the complex gain of the l -th path, whose amplitude is related to the path loss and reflection coefficient; and $n(t)$ is zero-mean additive white Gaussian noise (AWGN) with power spectral density $N_0/2$.

In long-range scenarios, the LoS path signal is weak. Taking free-space propagation over 200 km as an example, with a center frequency of 2.42 GHz, the path loss is approximately 148 dB. Under such conditions, strong adjacent reflected components (strong near-LoS multipath) from the ground or buildings can easily create false main peaks in the correlation function whose amplitudes exceed the true LoS peak, making it difficult for traditional ToA estimation algorithms to correctly lock onto the first arrival path, thereby causing ranging failure. In this paper, within the propagation range of 10 m to 200 km, based on the system positioning accuracy requirements, the required system ranging root-mean-square (RMS) error is better than 5 m.

In this paper, the ToA estimation error is calculated with the speed of light taken as $c \approx 3 \times 10^8$ m/s. The ranging accuracy requirement is equivalent to the ToA estimation error satisfying the condition of Eq. (2):

$$\text{RMS}_{\text{ToA}} = \frac{\text{RMS}_d}{c} < \frac{5}{3 \times 10^8} \approx 16.7 \text{ ns} \quad (2)$$

As previously noted, relying solely on high sampling rates or complex filtering is ineffective. With a chip rate of 32 Mcps, the single chip width is given by Eq. (3):

$$T_c = \frac{1}{32 \times 10^6} = 31.25 \text{ ns} \quad (3)$$

The chip width in Equation (3) limits the time resolution capability of conventional correlators. Relying solely on a high sampling rate or complex filtering makes it difficult to achieve the required ToA estimation accuracy. This paper deeply integrates the signal architecture prior information with a multi-stage estimation algorithm, breaking through the limitation of sub-chip fine estimation, and ultimately achieves a ToA resolution better than 16.7 ns.

III. DESIGN OF SYSTEM-AWARE HIGH-PRECISION TOA ESTIMATION ALGORITHM

The core of the proposed algorithm involves the four-dimensional orthogonal architecture design and a three-stage estimation process. The architecture provides search priors to compress the search window to the microsecond level. Building on this, an improved SNR-adaptive CLEAN soft-amplitude mechanism extracts effective multipath components, followed by three-point parabolic fitting in the LoS neighborhood for sub-chip fine estimation.

A. Scheduling-Guided Coarse Acquisition

The coarse acquisition algorithm extracts deterministic prior knowledge embedded in the waveform-specifically, static time slot assignments and hopping sequences-to shrink the acquisition window from the entire frame period (15 ms) to the microsecond level. Let ground station m be statically assigned to the $i_m \in \{0, 1, 2, 3\}$ -th primary slot and adopt a predefined hopping sequence κ_k . The start time of signal transmission for station m is defined as Eq. (4):

$$t_m = i_m \cdot T_{slot}, T_{slot} = 3.75 \text{ ms} \quad (4)$$

Within this primary slot, station m transmits signals according to the pre-assigned hopping sequence $\{\kappa_1, \kappa_2, \dots\} \subset \{0, 1, \dots, 9\}$. For the k -th transmission, let the hopping sub-slot index be κ_k . The start time of the corresponding sub-slot is defined as Eq. (5):

$$\tau_{th,k} = \kappa_k \cdot T_{sub}, T_{sub} = 375 \mu s \quad (5)$$

We assume station m transmits the spread-spectrum signal within the interval $[t_m + \tau_{th,k}, t_m + \tau_{th,k} + T_s)$, where the signal duration $T_s = 250 \mu s$ and the guard interval is $125 \mu s$.

Considering system synchronization errors and propagation-delay jitter, the maximum timing uncertainty is set as $\delta = 30 \mu s$. Benefiting from the ‘‘Static Slot + Hopping Sequence’’ design, the acquisition window is compressed to $T_w = T_s + 2\delta = 310 \mu s$.

Using known scheduling information (i_m, κ_k) and the local spreading code $c(t)$, the sensor calculates the specific acquisition window $W_m^{(k)}$ as per Eq. (6):

$$W_m^{(k)} = [t_m + \tau_{th,k} - \delta, t_m + \tau_{th,k} + T_s + \delta] \quad (6)$$

Local spreading codes are generated following Gold and Real ZC sequence standards [21,22]. Within this window, the

cross-correlation function between the received signal $r(t)$ and the local reference code $c_{\text{ref}}(t)$ is computed with a step size $\Delta\tau$. The specific calculation method is given by Eq. (7):

$$R(\tau) = \int_{\tau}^{\tau+T_s} r(t) \cdot c_{\text{ref}}^*(t - \tau) dt, \quad \tau \in W_m(k) \quad (7)$$

The integration interval corresponds to one complete spread-spectrum signal period. The coarse estimate is determined by peak detection, identifying the maximum point of the correlation function, as shown in Eq. (8):

$$\hat{\tau}_{\text{coarse}} = \arg \max_{\tau \in W_m^{(k)}} |R(\tau)| \quad (8)$$

The output $\hat{t}_{\text{ToA}}^{(\text{coarse})} = \hat{\tau}_{\text{coarse}}$ serves as the initial value for the next stage.

B. Improved CLEAN Multipath Separation Method

Traditional CLEAN algorithms employ hard threshold strategies [13], which often misclassify distant, low-energy LoS components as noise, leading to the erroneous removal of valid information. Inspired by Schmidt et al. [23,24], we propose an SNR-Adaptive Soft-Threshold CLEAN algorithm. This method retains amplitude uncertainty during iterative subtraction, reduces over-suppression of weak paths, and accurately models the statistical characteristics of multipath and noise in the correlation domain. The correlation output model is given by Eq. (9):

$$R(\tau) \approx \sum_{l=0}^{L-1} \alpha_l \cdot \Lambda(\tau - \tau_l) + v(\tau) \quad (9)$$

where $\Lambda(\cdot)$ is the main lobe of the spreading code's autocorrelation function, $\alpha_l \in \mathbb{C}$ is the complex gain of the l -th path, $\tau_0 < \tau_1 < \dots < \tau_{L-1}$ are path delays, and $v(\tau)$ is the equivalent noise term.

The algorithm initializes the residual as $R^{(0)}(\tau) = R(\tau)$, the multipath set as $P = \Phi$, and the number of iterations as $i = 0$. On this basis, peak detection is performed to find the position of the global maximum in the residual, as shown in Eq. (10):

$$\tau_{\text{peak}}^{(i)} = \arg \max_{\tau} |R^{(i)}(\tau)|, a^{(i)} = R^{(i)}(\tau_{\text{peak}}^{(i)}) \quad (10)$$

where $\tau_{\text{peak}}^{(i)}$ denotes the peak time delay and $a^{(i)}$ represents the complex peak value at this position. The subsequent algorithm uses $|a^{(i)}|$ for signal-to-noise ratio judgment and threshold comparison, and leverages $a^{(i)}$ for the reconstruction and elimination of multipath components.

Noise power is estimated from the correlation-function region T_{tail} , which lies far away from the main lobe inside each time-hopping sub-slot. This estimation procedure introduces no extra system overhead. The noise variance estimation is given by Eq. (11):

$$\hat{\sigma}_v^2 = \frac{1}{N_{\text{tail}}} \sum_{\tau \in T_{\text{tail}}} |R^{(0)}(\tau)|^2 \quad (11)$$

where T_{tail} denotes the interval outside the signal window of the time-hopping slot, and N_{tail} is the corresponding number of

sampling points.

Considering the statistical detection theory and engineering robustness requirements, this paper sets a safety factor $\beta=3$ to calculate the signal-to-noise ratio adaptive stripping strength γ_i . γ_i is used to dynamically adjust the stripping strength in the residual update stage, and its calculation process is given by Eq. (12):

$$\gamma_i = \min\left(1, \frac{|a^{(i)}|}{\beta\hat{\sigma}_v}\right) \quad (12)$$

where $a^{(i)}$ is the peak amplitude detected in the i -th iteration, and $\hat{\sigma}_v$ is the estimated value of the noise standard deviation.

In this paper, the detected peak amplitude $a(i)$ is taken as the complex gain estimate of the i -th path, yielding $\hat{a}_i=a^{(i)}$. All complex gain estimates are uniformly stored in the path set P . During the CLEAN multipath separation process, a path is determined to be a strong path ($\gamma_i \rightarrow 1$) if $|a^{(i)}|$ is much larger than $\beta\hat{\sigma}_v$, in which case the algorithm performs a complete stripping operation. A path is identified as a weak path ($\gamma_i \ll 1$) when $|a^{(i)}|$ is close to or smaller than $\beta\hat{\sigma}_v$, and the algorithm only executes a partial stripping operation in this scenario. Finally, the residual update is achieved by subtracting the weighted normalized autocorrelation function, as detailed in Eq. (13):

$$R^{(i+1)}(\tau) = R^{(i)}(\tau) - \gamma_i \cdot \hat{a}_i \cdot \Lambda(\tau - \tau_{peak}^{(i)}) \quad (13)$$

where $\Lambda(\tau) = \frac{1}{E_c} \int_{-\infty}^{\infty} c(t)c(t-\tau) dt$ is the signal autocorrelation function.

Considering the typical multipath sparsity in the T-F-CDMA-TH architecture, the requirement for complete multipath separation, and the algorithm's robustness against overfitting, we set the maximum iterations $I_{\max} = 8$ and the stopping threshold $\delta_{\text{stop}} = 1.5\sigma_v$. Iteration stops when $I_{\max}$ or $|a^{(i)}| < \delta_{\text{stop}}$. All detected paths are sorted by delay τ_i^{peak} . To control the false alarm probability, the first path satisfying $|\hat{a}_i| > 3\sigma_v$ is selected as the initial LoS estimate $\hat{\tau}_{\text{LoS}}$ for fine estimation. This dual mechanism of low-threshold iterative stripping and high-threshold final judgment ensures effective suppression of strong multipath while avoiding noise peaks being misidentified as valid paths.

C. Sub-Sample Fine Estimation via Local Parabolic Fitting

The overall workflow of the proposed SA-ToA method is illustrated in Fig. 2. Based on the coarse estimate $\tau_{\text{first}} = \hat{\tau}_{\text{LoS}}$ from the improved CLEAN algorithm, we perform sub-sample fine estimation using local parabolic fitting. Parameters: Chip rate = 32 Mcps ($T_c = 31.25$ ns); ADC sampling rate = 128 MHz ($T_s = 7.8125$ ns). Since major multipath components have been stripped, the residual correlation function near τ_{first} exhibits local smoothness and unimodality, composed of the LoS autocorrelation main lobe and noise. We select three equidistant sampling points centered at τ_{first} : $\tau_- = \tau_{\text{first}} - T_s$, $\tau_0 = \tau_{\text{first}}$, $\tau_+ = \tau_{\text{first}} + T_s$. Let the corresponding normalized correlation values be $R_- = R(\tau_-)$, $R_0 = R(\tau_0)$, $R_+ = R(\tau_+)$. Assuming the correlation function in this neighborhood can be approximated by a quadratic polynomial, the fine delay estimate (vertex position) is given by Eq. (14):

$$\hat{\tau}_{fine} = \tau_{first} - \frac{T_s}{2} \cdot \frac{R_+ - R_-}{R_+ - 2R_0 + R_-} \quad (14)$$

Eq. (14) is used only if $R_+ - 2R_0 + R_- < 0$ and $|R_+ - R_-| > \epsilon$. Otherwise, $\hat{\tau}_{fine} = \tau_{first}$ is retained as the final ToA estimate.

Algorithm 1 System-Aware High-Precision ToA Estimation Algorithm Flow

```

1: Input:
   • Received signal  $r(t)$ 
   • Local reference spreading code  $c_{ref}$ 
   • Scheduling information (main slot index  $i_m$ , hopping sequence  $\kappa_k$ )
   • System parameters:  $T_{slot}$ ,  $T_{sub}$ ,  $T_s = 250 \mu s$ ,  $T_{sample} = 7.8125 ns$ 
   • Safety factor  $\beta = 3$ , maximum iterations  $N_{max} = 8$ 
2: Output: Fine ToA estimate  $\hat{\tau}_{fine}$ 
3: Calculate local search window based on scheduling info ( $i_m, \kappa_k$ ):
   
$$W_m^{(k)} = [t_m + \tau_{th,k} - \delta, t_m + \tau_{th,k} + T_s + \delta]$$

4: Compute sliding cross-correlation within this window:
   
$$R(\tau) = \int_{\tau}^{\tau+T_s} r(t) \cdot c_{ref}^*(t - \tau) dt, \quad \tau \in [\tau_{min}, \tau_{max}^{local}]$$

5: Estimate noise power:
   
$$\hat{\sigma}_v^2 = \frac{1}{N_{tail}} \sum_{\tau \in T_{tail}} |R^{(0)}(\tau)|^2$$

6: Initialize:  $R^{(0)}(\tau) \leftarrow R(\tau)$ ,  $P \leftarrow \emptyset$ ,  $n \leftarrow 0$ .
7: Repeat
8:   Find max peak position and amplitude in  $R^{(n)}(\tau)$ :
   
$$\hat{\tau}_n \leftarrow \arg \max_{\tau} R^{(n)}(\tau), \quad A_n \leftarrow R^{(n)}(\hat{\tau}_n)$$

9:    $\gamma_n \leftarrow \min \left( 1, \frac{|A_n|}{\beta \hat{\sigma}_v} \right)$ 
10:   $\alpha_n \leftarrow A_n$ 
11:  if  $|A_n| \leq \beta \hat{\sigma}_v$  then
12:    Break (Exit early, do not execute steps 11–13)
13:  else
14:     $P \leftarrow P \cup \{(\hat{\tau}_n, \alpha_n)\}$ 
15:     $R^{(n+1)}(\tau) \leftarrow R^{(n)}(\tau) - \gamma_n \cdot \alpha_n \cdot \Lambda(\tau - \hat{\tau}_n)$ 
16:     $n \leftarrow n + 1$ 
17:  end if
18: Until  $n \geq N_{max}$ 
19: Sort  $P$  in ascending order by  $\hat{\tau}$ :  $P_{sorted} \leftarrow \text{sort}(P, \text{by } \hat{\tau})$ 
20: Select the first path satisfying  $|\alpha_k| > 3\hat{\sigma}_v$  as coarse estimate:
   
$$\hat{\tau}_{coarse} \leftarrow \min\{\hat{\tau}_k \mid (\hat{\tau}_k, \alpha_k) \in P, |\alpha_k| > 3\hat{\sigma}_v\}$$

21: Extract three points:
   
$$R_{-1} = R(\hat{\tau}_{coarse} - T_s^{sample}), \quad R_0 = R(\hat{\tau}_{coarse}), \quad R_{+1} = R(\hat{\tau}_{coarse} + T_s^{sample})$$

22: Calculate fine delay:
   
$$\hat{\tau}_{fine} \leftarrow \hat{\tau}_{coarse} - \frac{T_s^{sample}}{2} \cdot \frac{R_{+1} - R_{-1}}{R_{-1} - 2R_0 + R_{+1}}$$

23: Return  $\hat{\tau}_{fine}$ 

```

Fig.2. Flowchart of the System-Aware High-Precision ToA Estimation Algorithm.

D. Theoretical Performance Analysis: Cramér-Rao Lower Bound

There exists a theoretical limit on the Time of Arrival (ToA) estimation accuracy, which is defined by the Cramér-Rao Lower Bound (CRLB) [25,26,27]. For a single-path spread spectrum signal over an Additive White Gaussian Noise (AWGN) channel, the CRLB for time delay estimation is given by Eq. (15):

$$\text{var}(\hat{\tau}) \geq \frac{1}{8\pi^2 \cdot \text{SNR} \cdot B_{rms}^2} \quad (15)$$

where SNR denotes the post-despread signal-to-noise ratio (linear value), and B_{rms} is the root-mean-square bandwidth of the signal, whose definition is given by Eq.(16).

$$B_{rms}^2 = \frac{\int_{-\infty}^{\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{\infty} |S(f)|^2 df} \quad (16)$$

where $S(f)$ denotes the baseband signal spectrum. The system in this paper adopts a rectangular power spectrum with a radio frequency (RF) double-sided bandwidth of $B_{RF} = 40$ MHz (at a center frequency of 2.42 GHz), corresponding to an equivalent

baseband single-sided bandwidth of $W=B_{\text{RF}}/2=20$ MHz. For this type of spectrum shape, its root-mean-square bandwidth is given by Eq.(17):

$$B_{\text{rms}} = \frac{W}{\sqrt{3}} \approx 11.55 \text{ MHz} \quad (17)$$

Substituting the above equation into the typical operating conditions, the post-despread signal-to-noise ratio is obtained as $\text{SNR}=16\text{dB} \approx 40$. Substituting $B_{\text{rms}} \approx 11.55$ MHz and $\text{SNR}=16\text{dB} \approx 40$ into Eq. (15), the lower bound of the time delay estimation variance can be derived $\text{var}(\hat{\tau}) \geq \frac{1}{8\pi^2 \times 40 \times (11.55 \times 10^6)^2} \approx 2.39 \times 10^{18} \text{ s}^2$ with the corresponding standard deviation $\hat{\sigma}_{\tau} \approx 1.55$ ns, from which the theoretical limit of ranging, i.e., the CRLB, is obtained. This value represents the theoretical lower bound of the time delay estimation variance on the premise that the first-arriving path is correctly detected. It reflects the physical limit determined by the signal bandwidth and signal-to-noise ratio, and does not include the impact of the first-path detection probability on the system performance. The derivation is given by Eq. (18):

$$\sigma_d = c \cdot \hat{\sigma}_{\tau} \approx 3 \times 10^8 \times 1.55 \times 10^{-9} \approx 0.464 \text{ m} \quad (18)$$

This value represents the physical limit determined by bandwidth and SNR, assuming the first path is correctly detected. It does not account for the probability of first-path detection failure. In practice, whether the weak first path can be detected amidst strong reflections and noise critically affects system performance. The proposed SA-ToA method primarily enhances the first-path detection probability through scheduling-guided acquisition and adaptive soft-threshold CLEAN. If the first path is successfully detected, the estimation accuracy can approach the CRLB. If detection fails, delay estimates can produce errors of tens of meters. Quantitative verification of this advantage is provided in the subsequent simulation experiments .

IV. PERFORMANCE ANALYSIS AND SIMULATION VERIFICATION

To systematically evaluate the SA-ToA method, we conducted simulations on the MATLAB platform strictly adhering to the system model defined in Section 2. Parameters: Sampling rate $f_s = 128\text{MHz}$, Chip rate $R_c = 32\text{Mcps}$, Frame length $T_{\text{frame}} = 15\text{ms}$. Spreading codes: Gold (4095) and repeated Zadoff-Chu (127) (denoted as Real ZC). To simulate realistic environments, we introduced fractional sampling delays (± 0.1 samples), timing jitter (± 2 samples), and AWGN. SNR is defined post-de-spreading. Monte Carlo trials (100 runs per scenario) were performed for short-range (10–100 m) and long-range (100–200 km) scenarios, with the random seed fixed at 2025 for reproducibility. Table 1 lists the multipath channel parameters.

TABLE I MULTIPATH CHANNEL PARAMETERS.

Channel Type	Delays (ns)	Gains
		(relative to main path)
LoS	0	1.0

NLoS1	80, 200	0.5, 0.03
NLoS2	165, 300, 450	0.03, 0.1, 0.02

The multipath parameters listed in Table I are simplified deterministic test cases. They are constructed to evaluate algorithm performance under controlled multipath configurations with clear physical interpretations. Although simplified, these scenarios are motivated by typical propagation conditions observed in land-mobile radio environments:

- 1) LoS: Serves as the baseline for evaluating best-case performance.
- 2) NLoS1: Models a ground-reflection-dominated scenario. The 80 ns path (gain 0.5) approximates a ground-surface reflection, with gain consistent with typical reflection coefficients [28]; the 200 ns path (gain 0.03) represents a weak secondary reflection. This scenario resembles open rural or suburban environments with moderate multipath.
- 3) NLoS2: Models a vegetation/terrain-blockage scenario. The 165 ns path (gain 0.03) represents a severely attenuated direct path due to partial foliage or terrain occlusion 3GPP TR 38.901[29], foliage loss model; and IEEE TAP 2020 suburban vegetation measurement[30]; the 300 ns (gain 0.1) and 450 ns (gain 0.02) paths represent ground/building reflections. This scenario resembles suburban or urban-fringe environments with strong reflections masking a weak first arrival.

A. Comparative Analysis with Existing Long-Range Positioning Technologies

Table 2 compares SA-ToA with typical long-range positioning systems. DME, using narrowband pulse-pair ranging [31], suffers from poor anti-multipath and anti-noise capabilities, with ranging errors >100 m within 400 km. eLORAN, utilizing low-frequency ground waves [32], experiences daytime positioning biases >10 m beyond 1000 km due to ionospheric disturbances. LEO satellite signals [33,34] offer theoretical sub-meter CRLB but require complex channel estimation and synchronization modules, leading to high hardware complexity. In contrast, the SA-ToA method, based on system-algorithm synergy, achieves ranging accuracy better than 5 m at 200 km (LoS, $\text{SNR} \geq 0$ dB).

TABLE II PERFORMANCE COMPARISON OF DIFFERENT LONG-RANGE POSITIONING TECHNOLOGIES.

Technology	Maximum Range	Ranging Principle	Typical Ranging Accuracy RMS (m)	User Response Required	User End Complexity
DME(Distance Measuring Equipment)	$\leq 400\text{km}$	Pulse Pair	100–500	Yes	Medium

eLoran	Regional (>1000 km)	Low-Frequency Group and Wave Communication	10–50	No	Medium
LEO Satellite Signals	Global	Navigation Signal Ranging	<1 (Theoretical)	No	High
SA-ToA	10m~200km	T-F-CDM A-TH + S A-ToA	3–5(LoS, SNR ≥ 0dB)	No	Medium

B. Near-Field Ranging Performance Analysis

In the short-range scenario (10–100 m), this paper evaluates the ToA estimation accuracy over LoS, NLoS1, and NLoS2 channels at SNR = 40, 50, and 60 dB. To provide a performance baseline, Peak Detection and Standard CLEAN are also evaluated under identical conditions. Table III presents the RMS ranging results at SNR = 60 dB averaged over 10–100 m for Gold code.

In the simulations, the earliest valid peak detection strategy is adopted for NLoS channels. The first-path delays of the NLoS1 and NLoS2 channels are 80 ns and 165 ns, respectively, corresponding to the ground-truth arrival times used to compute ranging errors. These delay values are not provided to the algorithm; peak detection is performed solely based on the received signal.

Over the LoS channel, the SA-ToA method achieves an RMS of 1.65 m, indicating no systematic bias. Over the NLoS1 channel, the SA-ToA method effectively suppresses the strong early-arriving reflection interference via the CLEAN soft threshold, yielding an RMS of 1.76 m. Over the NLoS2 channel, although the first-path gain is as low as 0.03, which causes the first path to be submerged by noise at certain moments, the absolute threshold priority detection mechanism of the SA-ToA method can still capture this weak path, achieving an RMS of 2.00 m.

(The above values correspond to the Gold-code results in Table III; the Real ZC sequence shows similar trends and is omitted for brevity.)

TABLE III SHORT-RANGE RMS PERFORMANCE COMPARISON (SNR = 60 DB, GOLD CODE, AVERAGED OVER 10 - 100 M)

Channel	Peak RMS (m)	CLEAN RMS (m)	SA-ToA RMS (m)
LoS	2.90	2.90	1.65
NLoS1	2.41	2.41	1.76
NLoS2	43.43	2.04	2.00

Note: RMS values are averaged over the four measured distances (10, 30, 50, and 100 m). The Real ZC sequence exhibits similar trends and is omitted for brevity. The individual per-distance results are shown in the simulation data; the averaged values are presented here for compactness.

In LoS and NLoS1, CLEAN produces RMS nearly identical to Peak Detection because its fixed hard threshold ($0.2 \times$ peak magnitude) rejects weak secondary paths, causing the algorithm to fall back to peak detection. In NLoS2, Peak Detection yields 43.43 m, indicating it locks onto a strong reflected path (gain 0.1) rather than the true first path (gain 0.03). CLEAN achieves 2.04 m, comparable to SA-ToA (2.00 m) in this short-range high-SNR scenario. However, this superficial similarity does not guarantee correct first-path identification; the CLEAN algorithm may still lock onto the strong reflection in some trials, and its performance is expected to degrade at lower SNR or longer ranges.

Fig. 3 further validates the ToA estimation accuracy of Gold code and Real ZC code under LoS channels. At short distances of 10-100 m and SNR = 60 dB, the RMS for Gold code in the LoS channel is 1.62 m, and for Real ZC sequence, it is 1.63 m. The ToA estimation accuracy of the two signals is close under LoS conditions.

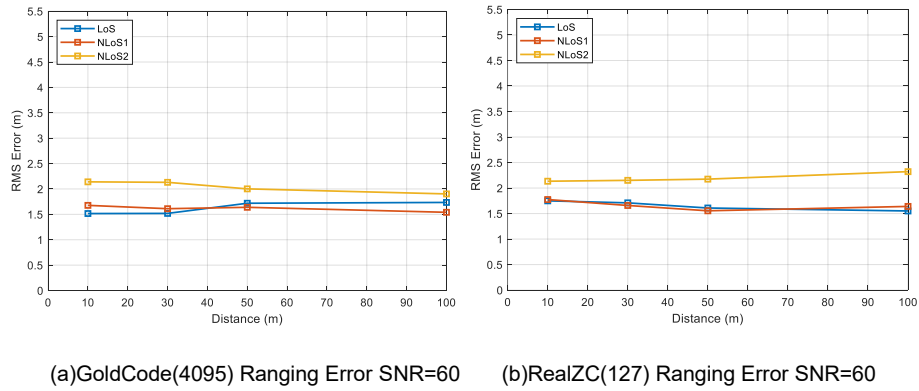
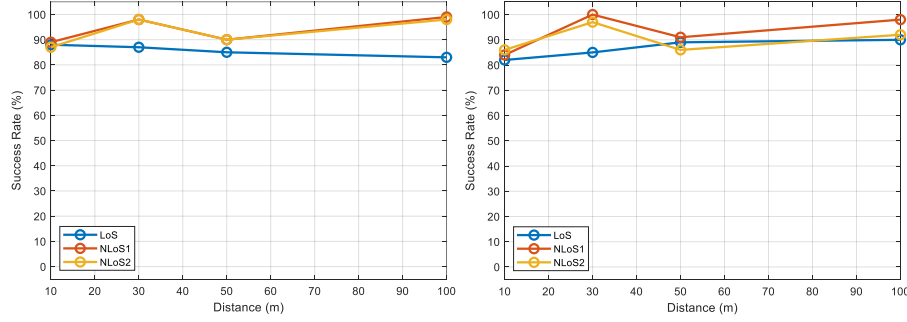


Fig. 3. Short-Range Ranging Error.

As shown in Fig. 4, for the two code types designed in this system, the estimation availability of Gold code in the NLoS1 channel (94.5%) is slightly higher than that of Real ZC (94%). In the more challenging NLoS2 channel, the estimation availability for both code types exceed 90%, demonstrating the effectiveness of the CLEAN multipath mitigation algorithm. Theoretically, Gold code has lower cross-correlation sidelobes, potentially offering better stability in complex multipath environments. Therefore, Gold code can be preferentially considered in engineering applications, while the appropriate code type can be selected based on specific scenario requirements.



(a)GoldCode(4095)Ranging estimation availability SNR=60 (b)RealZC(127)Ranging estimation availability SNR=60

Fig. 4. Short-Range Ranging estimation availability.

As shown in Fig. 5, under short-range ranging conditions, the error distributions for both Gold code and Real ZC sequence designed in this paper are close to Gaussian, exhibiting no significant systematic bias.

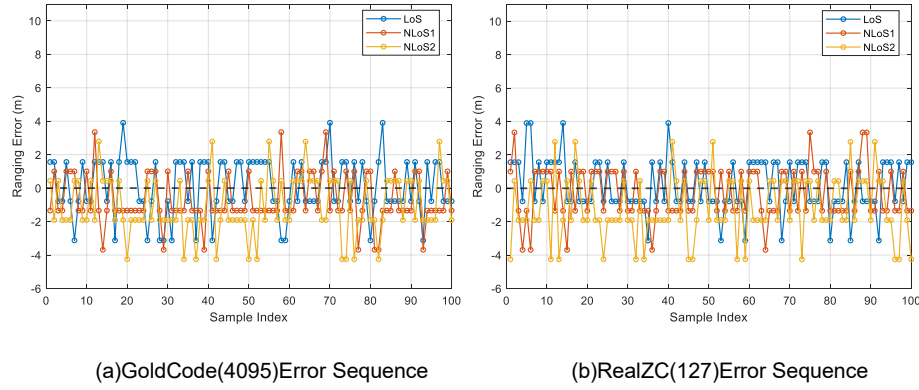


Fig. 5. Short-Range error sequences.

C. Long-Range System Capability Analysis

In Section 2.4, the CRLB of ToA estimation was derived as 0.46 m under ideal single-path conditions (40 MHz bandwidth, 16 dB de-spread SNR). Since practical long-range positioning systems often operate in much lower SNR regimes, we evaluate the proposed algorithm under more challenging conditions: 0 dB and 5 dB.

Monte Carlo simulations were conducted for 100 km and 200 km scenarios under low SNR and multipath interference. Table IV summarizes results at 100 km, SNR = 5 dB, comparing SA-ToA with Peak Detection, Narrow Correlator, Traditional CLEAN, and MEDLL (all using Gold code).

As reported in Table IV for CLEAN and MEDLL, a method may achieve 100% estimation availability in NLoS2 yet still produce large RMS errors (52.73 m and 91.91 m, respectively), because it has locked onto a strong reflected path rather than the true first arrival. In contrast, SA-ToA achieves both 100% estimation availability and a substantially lower RMS error (5.00 m), indicating that it not only converges reliably but also correctly identifies the first path. The distinction between estimation availability and first-path detection accuracy is further examined in the ablation study through a comparative analysis of RMS

errors, where the reduction from 52.73 m (traditional CLEAN) to 5.00 m (SA-ToA) serves as an indirect but quantitative measure of improved detection performance.

TABLE IV LONG-RANGE RANGING PERFORMANCE COMPARISON (100 KM, SNR = 5 dB, GOLD CODE)

Channel	Method	Bias(m)	RMS(m)	95% Error(m)	Estimation Availability (%)
LoS	Peak	2.38	5.65	11.0	100
	Narrow	1.96	4.45	8.7	100
	CLEAN	2.41	5.61	10.9	100
	MEDLL	2.25	5.28	10.3	100
	SA-ToA	2.38	4.00	7.8	100
NLoS1	Peak	12.34	27.24	53.2	100
	Narrow	11.05	24.37	47.6	100
	CLEAN	12.28	27.10	52.9	100
	MEDLL	12.09	26.68	52.1	100
	SA-ToA	2.33	4.93	9.6	100
NLoS2	Peak	45.21	92.50	180.7	100
	Narrow	43.79	89.57	175.0	100
	CLEAN	25.77	52.73	103.0	100
	MEDLL	44.94	91.91	179.6	100
	SA-ToA	2.64	5.00	9.9	100

NOTE: Estimation availability refers to the percentage of Monte Carlo trials in which the algorithm converges to a finite estimate without numerical failure (e.g., divergence or NaN outputs).

As indicated by the data in the table, the SA-ToA method achieves a 100% estimation availability under all test conditions, which demonstrates that the method possesses an extremely high robustness in the long-range and weak-signal environment with no divergence or failure cases observed. Over the LoS channel, the RMS of the SA-ToA method reaches 4.00 m; considering residual multipath, ionospheric perturbations and the finite sampling rate, this 4-m accuracy is very close to the theoretical CRLB limit. Conventional methods suffer from a sharp performance degradation due to correlation peak offset caused by strong reflective

paths over the NLoS1 and NLoS2 channels. In contrast, the SA-ToA method successfully locks onto the first-arriving path via the earliest valid peak strategy and adaptive threshold, enabling it to constrain the RMS within 5 m.

1) Statistical Significance and Convergence Analysis

To verify the statistical significance of SA-ToA's improvement, we performed paired t-tests and Wilcoxon signed-rank tests on error sequences (100 km, NLoS2, SNR = 5 dB). Table 5 shows all p-values are far below 0.001, confirming that SA-ToA's mean error is significantly lower than that of comparative algorithms.

TABLE V STATISTICAL SIGNIFICANCE TEST RESULTS (100 KM, NLoS2, SNR = 5 dB, GOLD CODE).

Comparison Algorithm	Paired t-test p-value	Wilcoxon Test p-value
Peak	1.2×10^{-15}	2.3×10^{-12}
Narrow	3.5×10^{-14}	5.6×10^{-11}
CLEAN	4.1×10^{-12}	1.8×10^{-9}
MEDLL	2.2×10^{-13}	3.9×10^{-10}

Convergence analysis (Fig. 6) at 100 km (LoS, SNR = 0 dB) indicates that the mean error stabilizes after approximately 30 trials, with reduced standard deviation fluctuations. This proves that 100 trials are sufficient for reliable statistics and that the method converges efficiently.

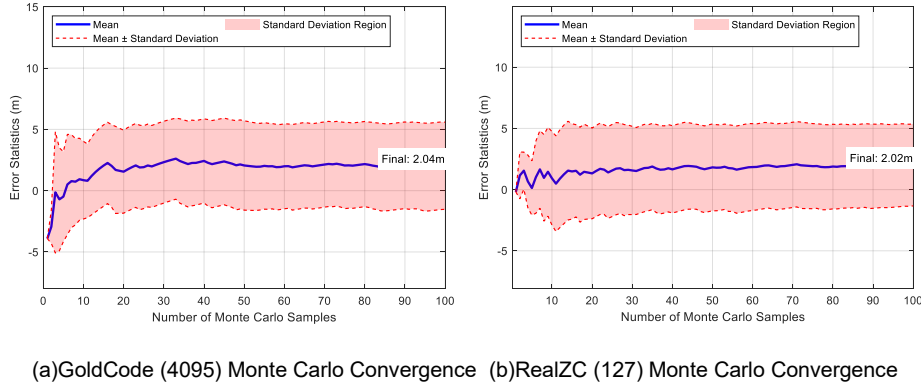


Fig. 6. Long-Range Ranging Monte Carlo Convergence Analysis.

2) Ablation Study: Effectiveness of Soft-Threshold Mechanism

To isolate the contribution of the SNR-adaptive soft-threshold mechanism, we compare the complete SA-ToA framework against conventional CLEAN under identical conditions (100 km, NLoS2, SNR = 5 dB). As shown in Table 4, both methods achieve 100% estimation availability. However, conventional CLEAN yields an RMS error of 52.73 m. By combining waveform-derived noise references and the adaptive soft-threshold mechanism, SA-ToA attains 5.00 m, corresponding to roughly 90 % error reduction.

This significant performance gap can be attributed primarily to the thresholding strategy, since the two methods share the same core structure of iterative multipath stripping. The only fundamental difference lies in how they determine which signal components to retain: conventional CLEAN applies a fixed hard threshold to the peak magnitude, whereas SA-ToA employs an SNR-adaptive soft threshold that dynamically adjusts based on the guard-interval-estimated noise floor.

To further substantiate this attribution, we examine two complementary lines of evidence:

As shown in Table 4 for far-field scenarios: under NLoS2 conditions, the first-path gain drops to merely 0.03. For conventional CLEAN, its fixed hard threshold often surpasses the amplitude of this weak first-arrival component, so the first path gets discarded. Consequently, the algorithm locks onto a strong reflected path (gain = 0.1), yielding large systematic error with RMS = 52.73 m. By comparison, the adaptive soft-threshold γ_i in SA-ToA retains the weak first-path component and enables correct identification, achieving RMS = 5.00 m.

Short-range results (Table 3): In NLoS1, where the first-path gain is as high as 0.5, both methods achieve comparable RMS performance. The hard threshold does not reject the strong first path in this case, confirming that the failure of conventional CLEAN in NLoS2 is due to the weakness of the first arrival rather than a general algorithmic deficiency.

Taken together, these results confirm that the soft-threshold mechanism is the dominant factor enabling SA-ToA to maintain robust first-path detection under low SNR and severe multipath conditions, while conventional hard-threshold CLEAN fails under the same circumstances.

While the complete SA-ToA framework includes additional components—such as scheduling-guided window compression and guard-interval-based noise estimation—these are enabling components that support the thresholding mechanism rather than being the primary source of the accuracy improvement. This is supported by the fact that conventional CLEAN already operates on the full 15 ms search window, and still fails in NLoS2, confirming that window compression alone cannot explain the observed performance gain.

3) *Static Ranging Performance under Different SNRs and Codes*

Fig. 7 compares Gold and Real ZC at SNR = 0 dB. At 200 km, Gold code (RMS < 4.5 m) outperformed Real ZC (RMS < 5.5 m). Conversely, at 100 km, Real ZC (RMS < 5.5 m) slightly outperformed Gold (RMS < 6.5 m). This suggests that the performance advantage of each code type is distance-dependent.

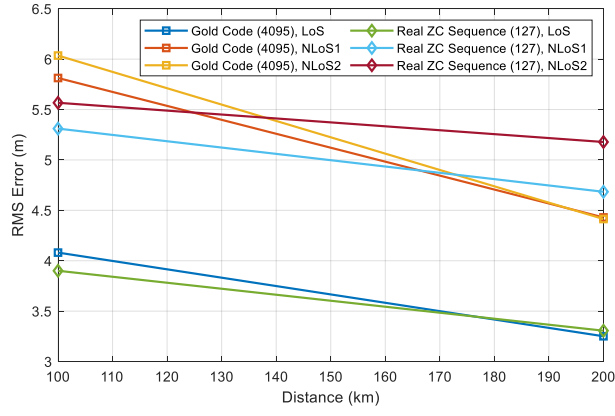


Fig. 7. Long-Range Ranging Accuracy.

4) Ranging Performance in Dynamic Doppler Scenarios

High-dynamic platforms (e.g., UAVs, high-speed ground vehicles) introduce Doppler shifts that distort correlation peaks. The Doppler shift is modeled as $f_d = f_c \cdot \frac{v}{c}$, where $f_c = 2.42$ GHz is the carrier frequency and v is the relative radial velocity. This frequency shift is applied to the baseband signal as a time-varying phase rotation: $s_d(t) = s(t) \cdot e^{j2\pi f_d t}$. No explicit Doppler compensation is performed at the receiver, allowing the evaluation of the algorithm's inherent robustness to frequency offsets. We simulated relative radial velocities $v \in [0, 500]$ m/s at 200 km (LoS, SNR = 0 dB).

Fig. 8 shows that for $v \leq 450$ m/s, RMS error remained stable around 2.15 m (fluctuation < 0.01 m), demonstrating strong robustness against subsonic and moderate supersonic Doppler effects. At 500 m/s, errors increased slightly to 2.21 m (Gold) and 2.29 m (Real ZC), still maintaining accuracy better than 2.3 m. This suggests that SA-ToA is robust to Doppler shifts in high-dynamic scenarios, indicating its potential applicability in disaster response or infrastructure-poor regions.

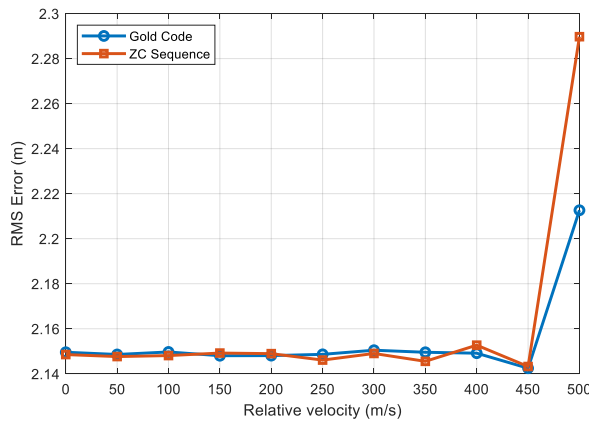


Fig. 8. Dynamic Long-Range Ranging Performance.

5) Performance Comparison with State-of-the-Art (SOTA) Methods

We benchmark SA-ToA against three representative SOTA lineages: deep learning/Transformer [14–15], subspace/super-resolution (MUSIC) [16], and interference-robust statistical detection (GLRT) [17]. Table 6 qualitatively compares

these methods across seven practical dimensions.

TABLE VI QUALITATIVE COMPARISON OF SA-TOA WITH STATE-OF-THE-ART TOA ESTIMATION METHODS.

Dimension	DL/Transformer [14,15]	MUSIC [16]	GLRT [17]	SA-ToA (Proposed)
Training Data Required	✓ (Large amount)	×	×	×
Multi-antenna Required	×	✓	✓	×
Prior Path Number Required	×	✓	×	×
Computational Cost	High (inference)	High (eigen-decomp.)	Medium	Low (FFT + iterative stripping)
Model Interpretability	Low (black-box)	Medium	High	High (waveform prior + threshold mechanism)
Robustness to Coherent Multipath	Medium (data-dependent)	Low	Medium	High (soft-threshold preserves first path)
Sensitivity to Noise Floor	Medium	High	Low	Low (adaptive threshold + guard interval)
Target Platform	GPU/Cloud	DSP/MCU with multi-antenna	DSP with multi-antenna	FPGA/DSP (single-antenna, <1 ms latency)

As summarized in Table VI, SA-ToA offers distinct advantages: no training data, single-antenna operation, low computational complexity (FFT + 8-iteration stripping), high interpretability, and robustness under extreme conditions.

For quantitative comparison under the most challenging configuration (100 km, NLoS2, SNR = 5 dB), we evaluated

GCC-PHAT, MUSIC, and GLRT under the same Monte Carlo setup. All three methods fail to produce valid ToA estimates. In contrast, SA-ToA achieves 100 % estimation availability with an RMS error of 5.00 m. The failure of MUSIC and GLRT is expected due to their multi-antenna and high-SNR requirements, which are not satisfied in our single-antenna, low-SNR setup. SA-ToA's key contribution lies precisely in its single-antenna, training-free, low-complexity design—characteristics that suggest its suitability for real-world GNSS-denied scenarios with severely limited hardware resources.

D. Computational Complexity Analysis

The complexity of SA-ToA mainly stems from three stages: coarse acquisition, CLEAN iterations, and parabolic fitting. The coarse acquisition window is $310\ \mu\text{s}$ ($N \approx 39,680$ samples at 128 MHz). Time-domain sliding correlation would demand about $N \times L \approx 1.27 \times 10^9$ operations ($L = 32,000$), a computational burden too heavy for embedded hardware. In contrast, FFT-accelerated frequency-domain correlation (Overlap-Save / Overlap-Add) lowers complexity to $O(N \log_2 N)$. Real-time implementation therefore becomes theoretically feasible.

Hardware estimation on platforms such as TI C66x DSP or Xilinx Kintex-7 FPGA suggests that the end-to-end latency per frame would be on the order of $< 1\ \text{ms}$, based on the above operation counts and typical clock frequencies of these devices. This estimated latency is comparable to the typical real-time requirement for UAVs ($< 10\ \text{ms}$), indicating that the proposed method is computationally feasible on mainstream DSP and FPGA platforms. These estimates provide a theoretical basis for future hardware prototyping and field testing.

E. Unified Comparison and Application Implications

SA-ToA exhibits stable performance across short and long ranges, with code-type dependent trade-offs. In short-range, high-SNR LoS conditions, both Gold and Real ZC codes achieve comparable RMS accuracy ($\sim 1.6\ \text{m}$) with near-zero bias. In long-range, low-SNR LoS conditions, Real ZC slightly outperforms Gold (3.66 m vs. 3.71 m), attributed to its superior autocorrelation sidelobes. However, in NLoS scenarios, Gold code demonstrates better robustness: for NLoS2, Gold achieves lower RMS (5.20 m vs. 5.57 m) and smaller bias (2.29 m vs. 2.71 m) due to its noise-like characteristics that suppress false peaks.

Based on these observations, Real ZC may be preferred for open-area or LoS scenarios (e.g., rural rescue), while Gold code may be more suitable for multipath-rich environments (e.g., urban canyons, disaster zones).

V. CONCLUSION AND FUTURE WORK

This paper proposes the SA-ToA scheme to meet the demand for wide-area high-precision PNT under GNSS-denied conditions. Most existing SOTA ToA estimators (deep-learning, subspace-based, statistical-detection methods) adopt a “fixed-waveform, receiver-only optimization” paradigm. This study breaks this paradigm and establishes a novel waveform-algorithm co-design framework for GNSS-denied ranging. The core innovation is twofold: on the waveform side, the T-F-CDMA-TH scheme embeds

system scheduling priors (static time slots and hopping sequences) directly into the transmitted signal, compressing the acquisition window from a full frame (15 ms) to 310 μ s; on the algorithm side, the guard-interval-tailored noise estimation enables an SNR-adaptive soft-threshold CLEAN mechanism that preserves weak first-path components while suppressing strong multipath. These innovations jointly construct a three-stage collaborative pipeline: scheduling-guided coarse acquisition, adaptive CLEAN multipath separation, and sub-sample fine estimation. This pipeline delivers ToA estimation with both high precision and strong robustness.

Simulation results demonstrate that in short-range scenarios (10–100 m), the RMS ranging error is better than 1.65 m. In long-range LoS conditions (200 km), the RMS error is better than 4 m. Even under severe multipath and extremely low SNR (0 dB), the estimation availability remains at 100%. Compared with representative SOTA methods including Transformer-based schemes, MUSIC and GLRT, SA-ToA exhibits clear practical strengths. It eliminates requirements for training datasets and multi-antenna hardware and works at moderate sampling rates, while achieving competitive or better accuracy under weak-signal and severe-multipath conditions. The proposed method provides a standalone, high-precision absolute ranging capability, overcoming the drift limitations of SLAM and IMU systems, and offering a robust solution for wide-area high-precision navigation. This work is especially relevant for infrastructure-free IoT-oriented scenarios: remote-area environmental monitoring, post-disaster ad-hoc sensor networks, and emergency-response missions operating without GNSS and fixed ground infrastructure.

Although our simulations include realistic impairments including fractional-sampling offset and timing jitter, all validation in this work relies on numerical simulation; real-world field experiments have not yet been performed. This limitation arises mainly from the preliminary status of our hardware-prototype development. Besides, it is technically challenging to fully control environmental variables such as dynamic multipath and atmospheric fading in outdoor measurement campaigns. To mitigate this gap toward practical deployment, we define a multi-step roadmap for future real-data validation:

(i) Prototype development: We will construct a radio prototype built upon Xilinx Kintex-7 FPGA and USRP hardware to implement the T-F-CDMA-TH waveform and the full three-stage SA-ToA algorithm.

(ii) Controlled field tests: We plan to carry out ranging experiments in representative challenging scenarios: open-field LoS, urban-canyon and hilly NLoS environments. Tests will first cover distances up to 5 km (short-to-medium range); high-power amplifiers will later extend the test range to 200 km.

(iii) Public-dataset benchmarking: As an intermediate validation step, we will evaluate SA-ToA on open-source UWB ranging datasets (e.g., LTSV Dataset) for fair comparison against published algorithms.

These efforts will systematically verify the robustness of SA-ToA under real-world hardware imperfections and environmental uncertainties, providing a foundation for its potential deployment in GNSS-denied operations such as coordinated autonomous search-and-rescue missions and infrastructure-less disaster response.

447

448 **Availability of data and materials:** The simulation code supporting the conclusions of this article are openly available in the
 449 Zenodo repository, <https://sandbox.zenodo.org/records/511549>.

450 **Competing interests:** The authors declare no competing interests.

451

452 **DECLARATIONS**

453 **Ethics approval and consent to participate**

454 Not applicable. This study does not involve human participants, human data, human tissue, or animals.

455 **Consent for publication**

456 Not applicable. This manuscript does not contain any individual person's data in any form (including individual details, images or
 457 videos).

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461 **Competing interests**

462 The authors declare that they have no competing interests.

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467 **Authors' contributions**

468 Yuan Ma: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft,
 469 Visualization. Guifen Chen: Conceptualization, Methodology, Supervision, Project administration, Writing – review & editing.
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REFERENCES

- 476 1. Jarraya, I., et al.: “GNSS-denied unmanned aerial vehicle navigation: analyzing computational complexity, sensor fusion, and
 477 localization methodologies,” *Satell. Navig.*, 2025, 6, art. no. 9, doi: 10.1186/s43020-025-00162-z
- 478 2. Zhang, J., Zhou, H., Xiao, Y., Li, X., Li, H., Chen, Y., and Luo, Z.: “Adaptive elite ant colony optimization for track planning in
 479 gravity-aided navigation with multi-feature fusion,” *Def. Technol.*, 2025, doi: 10.1016/j.dt.2025.11.011
- 480 3. Liu, Y., Yan, X., Liu, Q., An, T., and Dai, J.: “Automatic modulation recognition of radio fuzes using a DR2D-based adaptive
 481 denoising method and textural feature extraction,” *Def. Technol.*, 2024, 34, pp. 328–338, doi: 10.1016/j.dt.2023.12.013
- 482 4. Kim, E., Lee, J., and Son, P.-W.: “Alternative eLoran pulses for early skywave mitigation,” *IEEE Access*, 2026, 14, pp. 6514–6524,
 483 doi: 10.1109/ACCESS.2026.3653451

5. Yang, M., Yan, B., Yang, C., et al.: "Research on the eLoran/GNSS combined positioning algorithm and altitude optimization," *Remote Sens.*, 2025, 17, (4), art. no. 633, doi: 10.3390/rs17040633
6. Zhao, Z., Zhao, Y., and Xi, X.: "A CNN-iTransformer spatiotemporal fusion model for long-term eLoran propagation prediction," *IEEE Antennas Wireless Propag. Lett.*, 2026, doi: 10.1109/LAWP.2026.3652273
7. Khalife, J., Neinavaie, M., and Kassas, Z.M.: "The first carrier phase tracking and positioning results with Starlink LEO satellite signals," *IEEE Trans. Aerosp. Electron. Syst.*, 2022, 58, (2), pp. 1487–1491, doi: 10.1109/TAES.2021.3113880
8. Zeng, G., Zhan, Y., and Xie, H.: "Channel allocation for mega LEO satellite constellations in the MEO-LEO networked telemetry system," *IEEE Internet Things J.*, 2023, 10, (3), pp. 2545–2556, doi: 10.1109/JIOT.2022.3213687
9. Shang, X., Sun, F., Liu, B., Zhang, L., and Cui, J.: "GNSS spoofing mitigation with a multicorrelator estimator in the tightly coupled INS/GNSS integration," *IEEE Trans. Instrum. Meas.*, 2023, 72, art. no. 8500112, doi: 10.1109/TIM.2022.3232668
10. Hu, R., Liu, J., Zhong, Y., et al.: "Fisheye image/GNSS based multimodal learning for GNSS NLOS/multipath correction: enhancing vehicle positioning in urban canyons for autonomous driving," *IEEE Trans. Veh. Technol.*, 2026, doi: 10.1109/TVT.2025.3639402
11. Li, K., He, J., El-Hajjar, M., and Yang, L.-L.: "Localization in reconfigurable intelligent surface aided mmWave systems: a multiple measurement vector based channel estimation method," *IEEE Trans. Veh. Technol.*, 2024, 73, (9), pp. 13326–13339, doi: 10.1109/TVT.2024.3393022
12. Ji, Q. and Wu, H.: "High-precision time-of-arrival estimation in HF sensor networks via multipath separation and independent tracking," *Sensors*, 2026, 26, art. no. 1640, doi: 10.3390/s26051640
13. Song, J., Xi, X., Pu, Y., Li, W., Bian, S., and Zhang, J.: "Personalized differential correction of eLoran propagation delay based on environmental parameter perturbations," *IEEE Trans. Antennas Propag.*, 2026, doi: 10.1109/TAP.2026.3651964
14. Chen, Y.L., et al.: "5G high-precision positioning in GNSS-denied environments using a positional encoding-enhanced deep residual network," *Sensors*, 2025, 25, (17), art. no. 5578, doi: 10.3390/s25175578
15. Coppens, D., Shahid, A., and De Poorter, E.: "UWB TDoA error correction using transformers: patching and positional encoding strategies," *IEEE Trans. Wireless Commun.*, 2026, 25, (6), pp. 7000–7013, doi: 10.1109/TWC.2025.3628168
16. Lee, S., et al.: "An energy efficient time-frequency transformation of chirp signals in multipath channels for MUSIC-based TOA estimation," *IEICE Trans. Commun.*, 2015, E98-B, (3), pp. 427–436
17. Barros, A. and Studer, C.: "Interference and multipath resilient ToA estimation," *arXiv preprint*, arXiv:2511.22629, 2025
18. Högbom, J.A.: "Aperture synthesis with a non-regular distribution of interferometer baselines," *Astron. Astrophys. Suppl. Ser.*, 1974, 15, pp. 417–426
19. Wei, Z.Q., Feng, Z.Y., Li, Y.H., et al.: "Terahertz joint communication and sensing waveform: status and prospect," *J. Commun.*, 2022, 43, pp. 3–10
20. Liu, Y., Wang, Z., Xu, J., et al.: "Near-field communications: a tutorial review," *IEEE Open J. Commun. Soc.*, 2023, 4, pp. 1999–2049, doi: 10.1109/OJCOMS.2023.3305583
21. Gold, R.O.: "Optimal binary sequences for spread spectrum multiplexing," *IEEE Trans. Inf. Theory*, 1967, 13, (4), pp. 619–621, doi: 10.1109/TIT.1967.1054048
22. Chu, D.: "Polyphase codes with good periodic correlation properties," *IEEE Trans. Inf. Theory*, 1972, 18, (4), pp. 531–532, doi: 10.1109/TIT.1972.1054840
23. Schmidt, R.O.: "Multiple emitter location and signal parameter estimation," *IEEE Trans. Antennas Propag.*, 1986, 34, (3), pp. 276–280, doi: 10.1109/TAP.1986.1143830

24. Chan, F.K.J., So, H.C., and Chan, Y.T.: "Efficient subspace-based algorithm for adaptive bearing estimation and tracking," *IEEE Trans. Signal Process.*, 2005, 53, (12), pp. 4449–4458, doi: 10.1109/TSP.2005.859279
25. Arash, M., Stupia, I., and Vandendorpe, L.: "Real-time CRLB based antenna selection in planar antenna arrays," *IEEE Trans. Wireless Commun.*, 2023, 22, (6), pp. 4043–4056, doi: 10.1109/TWC.2022.3222885
26. Wang, Y., Gui, S., Tian, Z., Huang, C., Liu, K., and Li, Z.: "A high-precision GNSS SAR imaging fusion method utilizing optimally matched satellites calculated by CRLB," *IEEE Trans. Geosci. Remote Sens.*, 2025, 63, art. no. 5801214, doi: 10.1109/TGRS.2025.3552103
27. Kay, S.M.: *Fundamentals of Statistical Signal Processing: Estimation Theory*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1993
28. ITU-R: "Propagation by diffraction," Recommendation ITU-R P.526-15, 2019
29. 3GPP: "Study on channel model for frequencies from 0.5 to 100 GHz," Technical Report TR 38.901, version 19.1.0, Release 19, 2025
30. Zhang, P., Yang, B., Yi, C., Wang, H., and You, X.: "Measurement-based 5G millimeter-wave propagation characterization in vegetated suburban macrocell environments," *IEEE Trans. Antennas Propag.*, 2020, 68, (7), pp. 5556–5567, doi: 10.1109/TAP.2020.2981726
31. Park, J., Park, S., Lee, S., Seo, J., and Kim, E.: "Toward high accuracy DME for alternative aircraft positioning: SFOL pulse transmission in high-power DME," *IEEE Trans. Aerosp. Electron. Syst.*, 2025, 61, (5), pp. 15087–15097, doi: 10.1109/TAES.2025.3578290
32. Kim, W., Son, P.-W., Park, S.G., Park, S.H., and Seo, J.: "First demonstration of the Korean eLoran accuracy in a narrow waterway using improved ASF maps," *IEEE Trans. Aerosp. Electron. Syst.*, 2022, 58, (2), pp. 1492–1496, doi: 10.1109/TAES.2021.3114272
33. Wang, M., et al.: "Integrated communication and navigation based on LEO satellite networks: a survey," *IEEE Internet Things J.*, 2025, 12, (22), pp. 46244–46268, doi: 10.1109/JIOT.2025.3601137
34. Yang, Y., Mao, Y., Ren, X., et al.: "Demand and key technology for a LEO constellation as augmentation of satellite navigation systems," *Satell. Navig.*, 2024, 5, (1), doi: 10.1186/s43020-024-00133-w



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