A Review of Satellite Passive Localization: Principles, Parameter Estimation, and Positioning Algorithms

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This paper provides a structured survey of satellite localization from the perspective of active and passive localization. After distinguishing the functional differences between active and passive localization, the paper focuses on satellite passive localization and reviews its main measurement mechanisms, including Time of Arrival (TOA), Time Difference of Arrival (TDOA), Frequency Difference of Arrival (FDOA), Angle of Arrival (AOA), and their joint variants. For each method, we summarize the basic principles, observation models, localization solution processes, and commonly used accuracy evaluation metrics such as the Cramér–Rao lower bound and the geometric dilution of precision. We further review parameter estimation techniques for TDOA and FDOA, as well as representative localization algorithms ranging from grid search and iterative solutions to pseudo-linear closed-form methods, convex optimization approaches, and emerging learning-based methods. Finally, the paper discusses key challenges in multi-parameter fusion, complex signal environments, and algorithmic robustness, and outlines future research directions for improving the performance and practicality of satellite passive localization systems.

***Index Terms*—Active and Passive Localization, Satellite Passive Localization, Parameter Estimation, Localization Solving Algorithms, Performance Analysis.**

I. Introduction

ACCURATE target localization is pivotal in both military and civilian systems. In the military domain, precise localization provides robust support for the deployment of precision-guided weapons; in the civilian domain, it offers reliable services and ensures safety for targets [1]–[6]. Based on the mechanism of interaction between the system and the target, satellite localization technologies are primarily categorized into two main types: active localization and passive localization.

Active localization systems actively transmit signals using devices such as radar and lasers to detect targets [7], [8], offering advantages like all-weather operation and high precision. However, active systems require the transmission of high-power signals, which makes them prone to revealing their locations. Consequently, they are susceptible to ”soft kills” from electronic jamming and ”hard kills” from anti-radiation missiles, severely compromising system survivability. In contrast, passive localization technology localizes targets by intercepting their radiated signals. Since the system itself does not emit electromagnetic waves, it possesses significant advantages such as long operating range and high concealment [9], [10]. This significantly enhances survivability in modern electronic warfare environments, making it a research hotspot in the field of electronic reconnaissance.

Passive localization technology is essentially the integration of localization methods and algorithms. Its implementation consists of two steps: first, measurement techniques are used to acquire the parameters of the radiation source and its signals to select the appropriate localization method; second, observation models are established to select effective localization algorithms. Recent high-tech regional conflicts have demonstrated that passive localization systems have become an integral component of modern integrated air defense, ground and maritime strikes, and long-range early warning systems. They occupy a strategic position in military electronic systems that increasingly emphasize covert operations.

Currently, passive localization methods primarily include Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA), Frequency Difference of Arrival (FDOA), and joint information localization [11]–[13]. Compared to ground and airborne platforms, satellite platforms offer advantages such as broad measurement coverage, high precision in position and velocity measurement, and strong signal processing capabilities. In particular, joint TDOA-FDOA localization using dual-satellite or multi-satellite systems can mitigate time difference ambiguity and resolve the multi-solution problem. This significantly improves localization accuracy and has become the dominant technical solution for satellite-based passive localization.

In recent years, several comprehensive surveys have appeared in the literature covering localization technologies in various domains, with a primary focus on indoor localization, active wireless network localization, and specific satellite localization technologies.

Regarding indoor and wireless network localization, Pandey and Agrawal provided a classification and evaluation of localization techniques for wireless networks (such as WLAN and Ad-hoc networks), focusing on measurement parameters such as Signal Strength (SS) and TOA [14]. Yassin et al. investigated theoretical approaches and applications for indoor localization, analyzing the performance of WLAN, Ultra-Wideband, and sensor fusion technologies in complex indoor environments [15]. Laoudias et al. further broadened the scope by surveying enabling technologies for network localization and navigation in cellular networks (including 5G), WLANs, and wireless sensor networks, specifically highlighting auxil-

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iary technologies such as mobility state estimation and indoor mapping [16].

In the field of satellite and integrated Ground-Air-Space (GAS) localization, existing research has largely concentrated on active or infrastructure-based localization services. Kubo detailed precise positioning technologies for global navigation satellite systems, covering Real-Time Kinematic (RTK), Precise Point Positioning (PPP), and PPP-RTK techniques, and highlighted the centimeter-level augmentation services of the Japanese Quasi-Zenith satellite system, which falls under the category of active satellite navigation [17]. With the development of Low Earth Orbit (LEO) satellites, Prol et al. conducted a survey on LEO-PNT (Positioning, Navigation, and Timing). Although they touched upon Doppler localization using signals of opportunity, the core focus remained on utilizing LEO constellations to provide PNT services [18]. Furthermore, Sallouha et al., looking at 6G networks, surveyed radio localization within integrated GAS networks, analyzing the localization capabilities of GAS base stations acting as anchors, primarily from the perspective of the evolution of the communication network architecture [19].

Despite the summaries provided by existing research on the aforementioned localization technologies, the primary focus has been on indoor environments, terrestrial wireless networks, or active navigation localization based on satellite signals. Currently, there is a scarcity of systematic surveys dedicated to Satellite Passive Localization—that is, the use of satellite platforms to passively detect and localize ground or aerial emitters. In particular, a complete summary and categorization of passive localization methods based on TDOA, FDOA, AOA, and TOA, covering their specific classifications, localization solution processes, and accuracy assessment frameworks, has yet to be presented in the literature.

II. Basic Principles of Satellite Passive Localization

This section primarily reviews the fundamental principles of the main methods for satellite passive localization, including Received Signal Strength (RSS), AOA, TOA, TDOA, FDOA, and hybrid localization methods combining multiple techniques, as illustrated in Fig. 1. The specific mechanisms of these methods are detailed in the following sections.

1) RSS

RSS localization is a range-based method that relies on measuring signal energy [20]–[22], as illustrated in Fig. 2. Its core principle utilizes the path loss model of electromagnetic wave propagation in free space to estimate the distance d between the transmitter and the receiver by measuring the received signal power. According to the Friis transmission equation, the relationship between the received power P_r, transmitted power P_t, antenna gains G_t, G_r, and carrier wavelength λ is expressed as:

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2}. \tag{1}$$

This equation indicates that the signal strength decays as a function of the square of the distance. Assuming the signal frequency, transmit power, and antenna gains are known, the distance d can be estimated by transforming the equation to obtain the path gain P_G:

$$P_G = \frac{P_r}{P_t G_t G_r} = \left(\frac{\lambda}{4\pi d}\right)^2. \tag{2}$$

The main advantages of the RSS method are its simple hardware requirements and the fact that it does not require time synchronization; it can be implemented using only a power detector, making it highly suitable for indoor localization in short-range, line-of-sight environments.

However, in satellite passive localization scenarios, RSS is rarely used as a standalone localization technique and is typically employed only as auxiliary information. The primary reasons are as follows: First, signals undergo severe attenuation over long distances, and signal strength drops sharply as distance increases, resulting in extremely low distance resolution at long ranges (such as satellite orbit altitudes). Second, multipath effects and shadowing in real-world environments cause significant fluctuations in signal strength, making distance estimates based on simple path loss models highly inaccurate. Furthermore, passive localization often targets non-cooperative sources, where the satellite usually does not know the target's initial transmit power P_t, rendering the direct calculation of distance using the RSS equation infeasible. Therefore, while RSS technology is well-suited for indoor or short-range localization, it struggles to meet the high-precision requirements of satellite-based ground reconnaissance.

Nevertheless, RSS plays a critical complementary role in hybrid fusion systems, particularly when primary observables are insufficient. For example, in geostationary earth orbit scenarios, AOA estimates often yield a set of potential locations (i.e., a line of position) rather than a unique point; in such cases, integrating RSS measurements provides a necessary distance constraint to resolve position ambiguity and pinpoint the target [21]. Additionally, for high-orbit or narrow-beam interference sources where multi-satellite TDOA is invalid due to visibility constraints, or where single-satellite Doppler methods degrade, the rate of change in RSS can be exploited via data-driven approaches to estimate the distance variation, thereby effectively supplementing the localization solution [20].

2) AOA

AOA localization is a direction-finding-based localization method [23], [24]. Its core principle involves calculating the target's position by measuring the direction angle of the radio signal arriving at the receiver's antenna array, utilizing the principle of triangulation, as illustrated in Fig. 3. The system uses high-precision directional antennas or antenna arrays to measure the azimuth and elevation angles of the target signal relative to the satellite's coordinate system. Assuming the target node coordinates are (x, y) and the reference node (satellite) coordinates are (x_i, y_i), the line connecting the target and the reference point forms an angle β_i with the X-axis. This angle is defined as the angle of arrival:

$$\tan\beta_i = \left(\frac{y - y_i}{x - x_i}\right). \tag{3}$$

TABLE I
CLASSIFICATION AND CHARACTERISTICS OF LOCALIZATION METHODS

Feature	Active Localization	Passive Localization
Target Participation	Target actively transmits signals; receiver locates target via signal measurement.	Target does not need to actively transmit signals; receiver passively receives signals for localization.
Communication Direction	Two-way communication.	One-way communication.
Signal Source	Target actively participates.	Target participation not required.
Applicable Scenarios	Target actively transmits signals.	Target naturally emits signals or reflects signals.
Advantages	High precision, good real-time performance, suitable for dynamic targets.	Target participation not required, suitable for covert reconnaissance.
Applications	GPS, BeiDou, Wi-Fi Indoor Localization.	Radar Monitoring, Aerospace Target Localization, Radio Reconnaissance.

Technology	Measurement Parameter	Localization Principle	Application Scenarios	Advantages	Limitations
RSS[20]-[22]	Received Signal Strength	Estimates distance by measuring signal strength combined with path loss models	Indoor Localization	Simple hardware	Severe signal attenuation
AOA[23], [24]	Signal Angle of Arrival	Measures arrival angle; localization via geometric triangulation	Radar Surveillance / Monitoring	No time synchronization required; Suitable for long-distance dynamic targets	Low accuracy (distance-dependent); High-precision antennas increase hardware cost and complexity
TOA[25], [26]	Signal Time of Arrival	Measures signal propagation time; calculates position based on geometric relationships	GNSS, Radar	High localization accuracy; Effective multi-satellite coordination	Requires strict time synchronization; High hardware complexity
TDOA[27]-[29]	Signal Time Difference	Measures the time difference of the signal arriving at different receivers; hyperbolic localization	Radio Monitoring, Radar Localization	Does not rely on transmitter-receiver synchronization; Suitable for dynamic targets	High requirement for time difference measurement precision
FDOA[30]-[33]	Signal Frequency Difference	Measures Doppler frequency shift difference; localization combines velocity and location relationships	Satellite / High-speed Target Localization	Higher localization accuracy; Suitable for detecting high-speed moving targets; High concealment (Covertness)	High requirement for frequency measurement precision

Fig. 1: Classification of Passive Localization Methods.

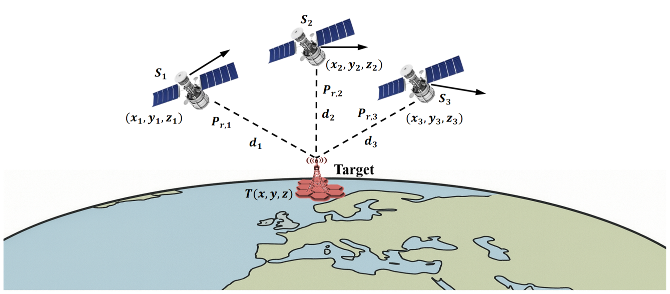

Fig. 2: Schematic diagram of Satellite RSS Passive Localization.

Geometrically, each measured angle of arrival β_i defines a ray (bearing line) pointing from the satellite to the target. The target's position is determined by the intersection of rays measured by two or more satellites.

The main advantage of this technology is that it does not require time synchronization, relying solely on angular information for localization, making it suitable for tracking long-distance dynamic targets. However, the AOA method has significant limitations: First, its localization accuracy decreases significantly with distance (angular errors are amplified over long ranges). Second, in complex satellite communication environments, multipath effects can severely interfere with the accuracy of angle measurements. Finally, to achieve high-precision angle measurement, satellites must be equipped with complex directional antenna arrays, which significantly increases the hardware cost and payload weight of the system.

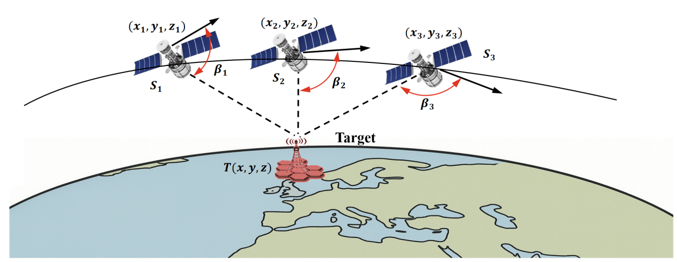

Fig. 3: Schematic diagram of Satellite AOA Passive Localization.

3) TOA

TOA localization is a range-based localization method [25], [26]. Its core principle involves calculating the target's position by measuring the signal propagation time from the source to the receiver, combined with geometric relationships, as illustrated in Fig. 4. The system establishes a distance observation equation based on the signal arrival time t_i recorded by the satellite, the transmission time t_0 of the target, and the speed of light c:

$$d_i = c \cdot (t_i - t_0). \tag{4}$$

Geometrically, this distance defines a sphere centered at the satellite. The target's coordinates are determined by the intersection of spheres from multiple satellites.

The main advantages of this technology are its high localization accuracy and effectiveness in multi-satellite coordination. However, the limitations of the TOA method are also significant: it requires strict time synchronization to ensure that t_0 and t_i share the same time reference, and the system often entails high hardware complexity. Particularly in satellite passive localization scenarios targeting non-cooperative sources, the core requirement of "strict time synchronization" cannot be met (since the transmission time t_0 of a non-cooperative target is unknown). Therefore, pure TOA methods are generally not directly applicable and are often converted into a TDOA framework to eliminate time synchronization errors.

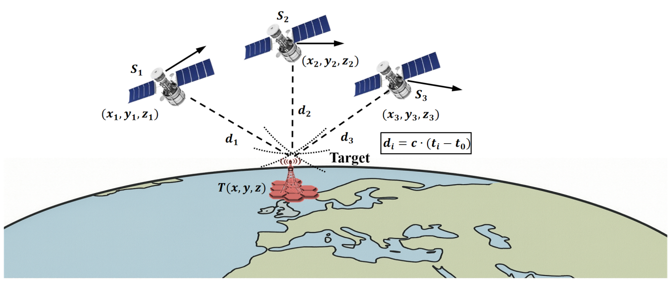

Fig. 4: Schematic diagram of Satellite TOA Passive Localization.

4) TDOA

Given that the TOA localization method requires strict time synchronization between the radiation source and the receiver, which is extremely difficult to achieve in satellite passive localization for non-cooperative targets, the TDOA technique is widely adopted to overcome this limitation [27]–[29]. The core idea of the TDOA method is to eliminate the unknown signal transmission time parameter by measuring the time difference of the same signal arriving at different satellites, thereby achieving precise localization without requiring synchronization between the transmitter and receiver, as illustrated in Fig. 5.

A typical three-satellite TDOA localization system consists of one master satellite (S_1) and two adjacent satellites (S_2, S_3). In a spatial Cartesian coordinate system, let the position of the target source be $T = (x, y, z)^T$, and the coordinates of the three satellites be $\mathbf{s}_j = (x_j, y_j, z_j)^T$ $(j = 1, 2, 3)$. Based on the propagation of signals at the speed of light c, the time difference of arrival $TDOA_{i1}$ between the i-th adjacent satellite and the master satellite can be converted into a range difference r_{i1}:

$$r_{i1} = c \cdot TDOA_{i1} = r_i - r_1 \quad (i = 2, 3), \tag{5}$$

where r_i and r_1 represent the geometric distances from the target to the i-th adjacent satellite and the master satellite, respectively. Generally, the distance r_j for any satellite j is explicitly defined as $r_j = \|\mathbf{s}_j - \mathbf{T}\|$.

In three-dimensional geometric resolution, each TDOA measurement (i.e., range differences r_{21} and r_{31}) defines a hyperboloid of revolution with the master satellite and the corresponding adjacent satellite as foci, denoted as c_1 and c_2, respectively. To uniquely determine the target's position, the Earth's surface is often utilized as an additional constraint. Typically, the Earth ellipsoid equation (e.g., $x^2/a^2 + y^2/a^2 + z^2/b^2 = 1$) is introduced as an elevation constraint surface. The intersections of these two hyperboloids with the Earth's surface form two curves, l_1 and l_2. Solving the system of equations essentially involves finding the intersection points of these curves. Typically, the curves l_1 and l_2 intersect at two points, T and T_1. Here, point T represents the true position of the target, while point T_1 is a false (or ambiguous) solution. It is worth noting that as the satellites move and the observation geometry changes, the solution for the true position T remains stable and convergent, whereas the false solution T_1 is typically divergent and unstable. This characteristic allows for the elimination of the ambiguous solution through multiple observations or prior information, thereby determining the unique position of the target.

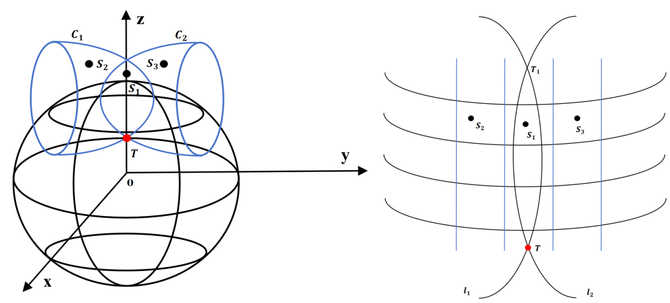

Fig. 5: Schematic diagram of Satellite TDOA Passive Localization.

5) FDOA

FDOA localization, also known as Doppler localization, is a method that utilizes the Doppler frequency shift effect caused by the relative motion between satellites and a ground radiation source [30]–[33]. As satellites travel at high speeds in orbit, the received signal frequency shifts due to the radial velocity component. The core principle of the FDOA method is to measure the frequency difference (Doppler difference) of the same signal arriving at different satellites, thereby determining the velocity vector and position information of the target relative to the satellites, as illustrated in Fig. 6.

A typical three-satellite FDOA localization system uses three LEO satellites to passively monitor the same target. Assuming the position coordinate of the stationary ground source T is $[x, y, z]^T$, and the position and velocity of the i-th satellite are $\mathbf{s}_i$ and $\mathbf{v}_i$, respectively. According to the Doppler principle, the Doppler frequency f_{d_i} received by the i-th satellite is related to the carrier frequency f_0 and the relative radial velocity:

$$f_{d_i} = \frac{f_0}{c} \cdot \frac{(\mathbf{s}_i - T) \cdot \mathbf{v}_i}{\|\mathbf{s}_i - T\|}. \tag{6}$$

By subtracting the Doppler frequencies received by two satellites (e.g., an adjacent satellite and the master satellite), an FDOA observation equation is obtained. Geometrically, each FDOA measurement defines a rotating iso-frequency difference surface. By combining multiple FDOA equations with the Earth's surface equation as a constraint, the intersection of these surfaces converges to a single point, which is the estimated position of the target T.

The main advantage of the FDOA method is that its localization accuracy improves with the increase of the target's or satellite's speed, making it highly suitable for localizing high-speed moving targets or using LEO satellites. Additionally, this method does not require time synchronization and possesses strong concealment and anti-interference capabilities. However, FDOA technology also has limitations: it requires extremely high precision in frequency measurement, and its performance is highly dependent on the relative geometric motion between the satellite and the target. If the target is stationary or moving slowly, or if the satellite's trajectory relative to the target is unfavorable (e.g., small radial velocity component), the localization accuracy will degrade significantly. Typically, FDOA is combined with TDOA methods to achieve complementary advantages and improve localization accuracy in complex scenarios.

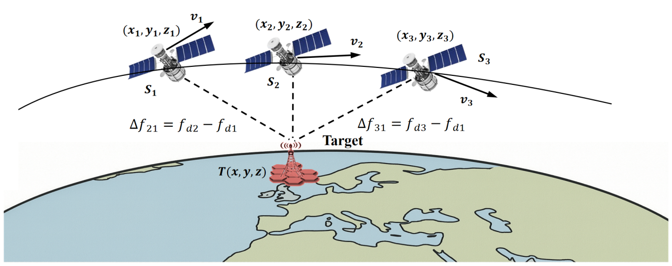

Fig. 6: Schematic diagram of Satellite FDOA Passive Localization.

6) Principles of Joint Localization Methods

In satellite passive localization systems, the single TDOA method is prone to time difference ambiguity or multiple solutions due to satellite geometry constraints, while relying solely on the FDOA method requires extremely high frequency measurement precision and is sensitive to the target's motion state. To overcome the limitations of single-mode systems, the joint TDOA and FDOA localization technique is widely adopted in academia [34]–[37]. This method utilizes multiple satellites (e.g., a three-satellite system) to simultaneously measure both time difference of arrival and frequency difference of Arrival. By increasing the number of independent observation equations, this approach not only effectively resolves the ambiguity problem but also significantly improves the localization accuracy and robustness of the system in complex environments, making it particularly suitable for precise localization of high-dynamic targets.

A typical three-satellite joint localization system constructs a set of joint observation equations by receiving signals from a ground radiation source $T = [x, y, z]^T$. Assuming the position vectors of satellites i and j are $\mathbf{s}_i, \mathbf{s}_j$ and their velocity vectors are $\mathbf{v}_i, \mathbf{v}_j$, respectively. The joint localization model solves for the target position by combining the TDOA range difference equation and the FDOA velocity difference equation. The core system of joint equations can be simplified as follows:

$$\begin{cases} r_{ij} = c \cdot TDOA_{ij} = \|\mathbf{s}_i - T\| - \|\mathbf{s}_j - T\| \\ \dot{r}_{ij} = \frac{c}{f_0} \cdot FDOA_{ij} = \frac{(\mathbf{s}_i - T)\cdot \mathbf{v}_i}{\|\mathbf{s}_i - T\|} - \frac{(\mathbf{s}_j - T)\cdot \mathbf{v}_j}{\|\mathbf{s}_j - T\|} \end{cases}, \quad (7)$$

where c is the speed of light, f_0 is the carrier frequency, and $\|\cdot\|$ denotes the Euclidean norm. Geometrically, the TDOA measurement defines a hyperboloid of revolution, while the FDOA measurement defines a rotating iso-frequency difference surface. By introducing the Earth ellipsoid equation as an elevation constraint, the joint solution of the above nonlinear equation system yields the unique intersection point of the iso-time-difference hyperboloid, the iso-frequency-difference surface, and the Earth's surface, thereby achieving high-precision 3D localization of the target T.

Pure TDOA localization suffers from severe accuracy degradation or even solution failure when the baseline is short or the target lies near the baseline extension. Although AOA localization requires only a single station for direction finding, its ranging capability is weak and heavily affected by distance. The joint AOA-TDOA localization technique fuses angle and time difference information to achieve superior performance through complementary advantages, making it particularly suitable for scenarios with few stations, such as single or dual-satellite systems [38]. Taking a two-station system as an example, assuming the coordinates of the master station S_1 and the slave station S_2 are known, the time difference of arrival of the signal from target $T = [x, y, z]^T$ is τ, and the angle of arrival measured by the master station is β. The joint localization model can be expressed as:

$$\begin{cases} r_{21} = c \cdot \tau = \|\mathbf{s}_2 - T\| - \|\mathbf{s}_1 - T\| \\ \tan\beta = \frac{y - y_1}{x - x_1} \end{cases}. \quad (8)$$

This system combines the hyperbolic equation (determined by TDOA) and the ray equation (determined by AOA), where their intersection yields the estimated position of the target. This method not only avoids the strict baseline length requirements of pure TDOA but also effectively improves the low accuracy of pure direction-finding localization in lateral regions.

For high-maneuvering or non-radially moving targets, pure FDOA localization exhibits large errors when the target's motion direction is perpendicular to the observation baseline, whereas AOA localization is insensitive to this issue. Joint AOA-FDOA localization combines Doppler frequency difference and angle of arrival information to achieve higher precision localization and tracking of moving targets [39], [40]. Assuming the velocity vectors of receivers S_1, S_2 are known, the received frequency difference is f_d, and the angle of arrival measured by the master station is β. The joint localization equation system is as follows:

$$\begin{cases} f_d = \frac{f_0}{c} \cdot \left(\frac{(\mathbf{s}_2 - T)\cdot \mathbf{v}_2}{\|\mathbf{s}_2 - T\|} - \frac{(\mathbf{s}_1 - T)\cdot \mathbf{v}_1}{\|\mathbf{s}_1 - T\|} \right) \\ \tan\beta = \frac{y - y_1}{x - x_1} \end{cases}. \quad (9)$$

Geometrically, FDOA defines an iso-frequency difference surface, and AOA defines an azimuth plane. The intersection of these surfaces with the Earth's surface determines the target's position. By exploiting the mobility of observation stations and the enhanced observability of the target, this method effectively resolves the accuracy divergence problem of single-mode localization systems under specific geometric configurations.

III. Performance Metrics for Localization Accuracy Analysis

In practical satellite passive localization systems, due to the influence of measurement noise, system biases, and geometric configuration, the estimated target position inevitably deviates from the true position. To quantitatively evaluate the performance of localization algorithms, metrics such as Bias, Root Mean Square Error (RMSE), Cramér-Rao Lower Bound (CRLB), and Geometric Dilution of Precision (GDOP) are commonly employed.

1) Bias

Bias is used to measure the accuracy of the localization estimation algorithm, reflecting the deviation between the expected value of the estimate and the true value. Assuming the true position of the target is $\mathbf{T} = [x, y, z]^T$, and the estimated position obtained from the n-th Monte Carlo simulation is $\hat{\mathbf{T}}^{(n)}$ (for a total of N simulations), the bias of the estimator is defined as the difference between the expectation of the estimate and the true position:

$$\text{Bias}(\hat{\mathbf{T}}) = E[\hat{\mathbf{T}}] - \mathbf{T} \approx \frac{1}{N}\sum_{n=1}^{N}(\hat{\mathbf{T}}^{(n)} - \mathbf{T}) \tag{10}$$

When N approaches infinity, if Bias $= 0$, the estimator is called unbiased. In practical systems, a non-zero bias typically indicates the presence of systematic errors in the observation data or inherent bias in the algorithm itself.

2) RMSE

RMSE is the most commonly used metric for measuring localization precision, comprehensively reflecting both the dispersion (variance) and the deviation (bias) of the estimates. RMSE is defined as the square root of the expected squared difference between the estimated value and the true value:

$$\text{RMSE}(\hat{\mathbf{T}}) = \sqrt{E[\|\hat{\mathbf{T}} - \mathbf{T}\|^2]} \approx \sqrt{\frac{1}{N}\sum_{n=1}^{N}\|\hat{\mathbf{T}}^{(n)} - \mathbf{T}\|^2}, \tag{11}$$

where $\|\cdot\|$ denotes the Euclidean norm. A smaller RMSE indicates that the localization result is closer to the true position, implying better algorithm performance.

3) CRLB

The CRLB provides a theoretical minimum lower bound for the variance of any unbiased estimator, serving as a crucial benchmark for evaluating the performance of localization algorithms. For any unbiased estimator $\hat{\mathbf{T}}$, its covariance matrix $\mathbf{C}_{\hat{\mathbf{T}}}$ satisfies the following inequality:

$$\mathbf{C}_{\hat{\mathbf{T}}} = E[(\hat{\mathbf{T}} - \mathbf{T})(\hat{\mathbf{T}} - \mathbf{T})^T] \geq \mathbf{J}^{-1}(\mathbf{T}), \tag{12}$$

where $\mathbf{J}(\mathbf{T})$ is the Fisher Information Matrix (FIM), defined as the negative expectation of the second-order partial derivative of the log-likelihood function of the observation data with respect to the parameter to be estimated (i.e., the target position $\mathbf{T}$):

$$\mathbf{J}(\mathbf{T}) = -E\left[\frac{\partial^2 \ln p(\mathbf{z}|\mathbf{T})}{\partial\mathbf{T}\partial\mathbf{T}^T}\right]. \tag{13}$$

Here, $p(\mathbf{z}|\mathbf{T})$ is the joint probability density function of the observation vector $\mathbf{z}$. The FIM reflects the amount of information about the target position contained in the observation data. The CRLB corresponds to the trace of the inverse of the FIM, i.e., CRLB $= \text{tr}(\mathbf{J}^{-1})$. If the variance of an estimator reaches the CRLB, it is termed a minimum variance unbiased estimator or an efficient estimator. In the design and analysis of satellite localization systems, CRLB is frequently used to predict the highest theoretically achievable localization precision under specific noise levels and geometric configurations.

4) GDOP

While CRLB provides the theoretical limit of precision, in engineering practice, GDOP is often introduced to intuitively describe the amplification effect of satellite geometric distribution on localization errors. GDOP is defined as the square root of the ratio of the trace of the localization error covariance matrix to the measurement error variance. In three-dimensional localization, GDOP can be expressed as:

$$\text{GDOP} = \frac{\sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2}}{\sigma_{meas}}, \tag{14}$$

where $\sigma_x^2, \sigma_y^2, \sigma_z^2$ are the estimation variance components of the target in the x, y, z directions, respectively, and σ_{meas} is the equivalent standard deviation of the measurement error. A smaller GDOP value indicates a better geometric configuration of the satellites relative to the target, making the localization error less prone to amplification. Conversely, if the satellites are nearly collinear, the GDOP value will increase sharply, leading to severe degradation of localization accuracy.

IV. Parameter Estimation Techniques for Satellite Passive Localization

Passive localization technology is essentially the deep integration of localization mechanisms and calculation algorithms. Specifically, achieving high-precision passive localization generally involves two critical steps: first, utilizing measurement techniques to extract observables (such as TDOA and FDOA) from the intercepted radiation source signals as accurately as possible; second, establishing mathematical models based on these observables and selecting effective algorithms to calculate the target's position. Among these, the precise estimation of the TDOA and FDOA between received signals is the primary prerequisite for realizing target source localization, as the estimation accuracy directly determines the accuracy of the final localization result [41], [42].

For the joint estimation of TDOA and FDOA parameters, traditional classic methods are mainly based on the cross ambiguity function. For narrowband signals, the narrowband cross ambiguity function serves as a maximum likelihood estimator, and its RMSE can approach the CRLB under high Signal-to-Noise Ratio (SNR) conditions. Specific implementation algorithms include the second-order time-domain cross-ambiguity algorithm and the second-order frequency-domain cross-ambiguity algorithm. While the time-domain algorithm is intuitive, its computational load increases dramatically with signal length. In contrast, the frequency-domain algorithm converts time-domain convolution into frequency-domain multiplication via Fourier transform, effectively reducing computational complexity, making it a widely used method in engineering applications [13], [43]–[45]. To further reduce computational load, Stein proposed a two-step search method (coarse estimation followed by fine estimation), significantly improving efficiency [46].

However, for wideband signals, the Doppler effect manifests as a time-scale stretching or compression of the signal rather than a simple frequency shift. In this case, the Wideband Cross Ambiguity Function (WBCAF) is required to jointly estimate the time difference and Scale Difference [47]–[49]. Calculating the WBCAF poses a significant computational challenge due to the need to stretch the signal at various scales. For discrete signals with unknown analytical forms, traditional resampling methods (interpolation and decimation) are computationally expensive. To address this, researchers have proposed methods based on the Wavelet Transform, utilizing the scaling properties of wavelet basis functions to approximate signal scaling, or leveraging cross-wavelet transform properties to reduce computation. Ho K.C. et al. proposed a fast scaling algorithm for discrete signals, which solved some computational issues but still required calculating the full WBCAF [50]. Additionally, some scholars proposed reconstructing continuous signals using the Sinc function and solving for the peak using Newton's iteration method. This approach has low computational cost but is sensitive to initial values and prone to converging to local maxima under low SNR [51].

With the increasingly complex electromagnetic environment and higher requirements for real-time performance, traditional parameter estimation technologies have continuously evolved. To improve estimation performance in non-Gaussian noise or interference environments, researchers have introduced the fourth-order maximum likelihood estimation algorithm, which utilizes higher-order statistics to suppress Gaussian background noise. Although it has high computational complexity, it significantly improves estimation accuracy. For wideband linear frequency modulated signals, Sharif et al. utilized the ridge feature of the ambiguity function to propose a method of searching for peaks along the ridge, simplifying the two-dimensional search into a one-dimensional search [52]. Furthermore, estimation algorithms based on the Fractional Fourier Transform have been proposed. By exploiting the energy concentration characteristics of signals in specific fractional domains, TDOA and FDOA are jointly estimated by solving a system of equations, significantly improving computational efficiency while maintaining accuracy [53]–[56]. The computational complexity comparison of various methods is shown in Table II, where N represents the signal length, N_0 represents the time delay search range, and a represents the frequency search range. As can be observed, the second-order frequency-domain cross-ambiguity algorithm is currently the method with the lowest computational complexity for TDOA-FDOA parameter estimation under conventional conditions.

In recent years, with the rapid development of artificial intelligence, intelligent algorithms have increasingly emerged in the field of passive localization. In the parameter estimation stage, researchers utilize deep learning networks to train "clutter libraries" for efficient clutter suppression [57], [58] and leverage the powerful feature extraction capabilities of neural networks to perceive weak signal features within large batches of data [59]. Additionally, data-driven intelligent methods are gradually demonstrating advantages over traditional model-driven approaches in signal transform domain processing and parameter estimation search optimization [60]–[62]. These studies indicate that combining advanced signal processing with artificial intelligence to optimize algorithms for different signal types and environmental characteristics is a key pathway to enhancing the overall performance of satellite passive localization systems.

V. Research on Passive Localization Solving Algorithms

After obtaining observables such as TDOA, FDOA, or AOA through parameter estimation, establishing and solving the system of localization equations is the key step to realizing target localization. Since these observation equations are typically highly nonlinear, traditional solving algorithms are mainly categorized into three types: grid search, iterative methods, and analytical methods (closed-form solutions). The Grid Search method obtains a global optimal solution by discretizing the area of interest and searching for the point with the minimum error, but it suffers from massive computational load and is limited by grid resolution.

Iterative algorithms linearize the nonlinear equations and iteratively solve them, offering high local convergence accuracy. Classic representatives include the Taylor Series Expansion and the Gauss-Newton method [63]–[67]. However, iterative methods are typically extremely sensitive to the selection of initial values; a large deviation in the initial guess can lead to convergence to local optima or even divergence. To address this issue, Maja Rosic et al. proposed an improved strategy that combines a Hybrid Genetic Algorithm with the Newton-Raphson method. This approach leverages the strong global search capability of the genetic algorithm to provide high-quality initial values, followed by the Newton-Raphson method for fine-tuning. This combination ensures global convergence while achieving higher localization accuracy than the traditional Least Squares method [68].

Analytical methods attempt to convert nonlinear equations into pseudo-linear ones by introducing auxiliary variables, thereby allowing direct solution using least squares. The Chan algorithm and the two-stage weighted least squares are classic representatives, which can approach CRLB in low-noise environments but degrade significantly under high noise [69]. Furthermore, to address non-convex optimization problems, relaxation algorithms based on semi-definite programming

TABLE II
COMPUTATIONAL COMPLEXITY OF TDOA-FDOA JOINT ESTIMATION ALGORITHMS

Algorithm	Computational Complexity
Second-order time-domain cross-ambiguity algorithm	$NN_0\left(4+\log_2 N\right)$
Second-order frequency-domain cross-ambiguity algorithm	$\frac{aN}{5}\left(2+\log_2 N\right)$
Fourth-order maximum likelihood estimation algorithm	$\frac{aNN_0}{5}\left(6+\log_2 N\right)$
Second-order frequency-domain cross-correlation	$\frac{aNN_0}{5}\left(2+\log_2 N\right)$

have been widely studied, offering good global convergence while maintaining computational efficiency [70]–[74].

In recent years, with the rise of artificial intelligence, utilizing neural networks to address difficulties in localization solving has become a new research hotspot [75]–[79]. Traditional solving methods often struggle when facing complex nonlinear equation systems or large measurement errors, whereas deep learning models demonstrate powerful capabilities in nonlinear fitting and feature extraction. Wu et al. pioneered the training of reciprocal neural networks to directly solve the localization problem of exogenous sources, bypassing complex mathematical derivations [80]. Addressing common issues such as asynchronization and multipath effects in TDOA measurements, scholars have designed long short-term memory networks to process sequential measurement data to reduce error impact [81], or employed Auto Encoders (AE) for data preprocessing to recover lost information and improve accuracy [82]. In more complex Direct Localization systems, neural networks have been used to design cost functions, effectively solving the immense computational challenge of constructing complex signal models in traditional methods [83]. These data-driven intelligent algorithms provide novel solutions for enhancing the robustness and accuracy of satellite passive localization in complex dynamic environments.

VI. Challenges and Future Directions

Although significant progress has been made in satellite passive localization technologies, numerous challenges remain when facing increasingly complex electromagnetic environments and higher precision requirements. Future research directions primarily focus on the following four aspects:

1. Deep Integration of Multi-Source Hybrid Localization Technologies: Current research often focuses on the combination of TDOA and FDOA. Future work should further explore the potential of combining more diverse localization techniques. For instance, introducing auxiliary information such as AOA, phase rate of change, or RSS can exploit the complementarity of different mechanisms. This helps to overcome the limitations of single techniques and improves system robustness and accuracy, especially in scenarios with few satellites or poor observation conditions.
2. Synergy of Heterogeneous Constellations and Geometry Optimization: With the rise of LEO mega-constellations, research should expand beyond satellite networking at a single orbital altitude. Future studies should deeply investigate the cooperative localization mechanism of heterogeneous orbits (High, Medium, and Low Earth Orbits), analyze the quantitative impact of increasing the number of satellites on localization gain, and summarize how to maximize localization efficiency by optimizing the geometric configuration of satellites (i.e., reducing the GDOP).
3. Advanced Signal Processing and Coherent Source Mitigation: In practical applications, signal detection and parameter estimation face the challenge of high computational complexity. In particular, coherent signals caused by multipath effects or interference can lead to rank deficiency in traditional algorithms (such as subspace-based algorithms), causing a sharp decline in performance or even failure. Recent AI-based approaches, such as Convolutional Neural Network-Long Short-Term Memory architectures for signal decorrelation [84] and multi-sensor fusion strategies integrating Extended Kalman Filter with Recurrent Neural Network [85], have shown effectiveness in mitigating coherent interference. Therefore, there is an urgent need to further integrate these low-complexity AI-driven algorithms into satellite passive localization systems.
4. Deepening the Application of Artificial Intelligence: Traditional model-driven algorithms encounter bottlenecks when dealing with non-linear and non-Gaussian noise environments. Future work should further explore data-driven approaches, especially the application of intelligent algorithms based on Deep Learning in passive localization. Learning-based frameworks [86] and deep learning models for TDOA-based asynchronous localization [81] have demonstrated superior capability in handling measurement errors and eliminating manual parameter tuning. Leveraging the powerful feature extraction and fitting capabilities of artificial intelligence can effectively solve the problems of parameter estimation and position calculation in complex dynamic scenarios.

VII. Conclusion

This paper presented an organized review of satellite localization with an emphasis on passive methods. We first clarified the distinction between active and passive localization, highlighting the unique applicability of passive techniques in covert or non-cooperative scenarios. The fundamental principles and geometric models of TOA, TDOA, FDOA, AOA, and joint localization methods were summarized, together with a unified accuracy evaluation framework. Parameter estimation techniques and major localization algorithms were also reviewed, including iterative solvers, pseudo-linear methods, convex relaxations, and emerging learning-based approaches.

Despite substantial progress, challenges remain in multi-source information fusion, signal processing under complex environments, and designing robust and efficient solvers for highly nonlinear localization equations. Future research should focus on developing hybrid localization architectures, improving robustness against environmental and measurement uncertainties, and exploring interpretable learning-based models that complement traditional geometric methods. Advancing these directions will be essential for achieving higher precision, improved reliability, and better scalability in satellite passive localization systems.

References

[1] S. Rehnmark, "Passive precision direction finding," *Journal of Electronic Defense*, vol. 13, no. 8, pp. 77–80, 1990.

[2] D. Adamy, "Radar warning receivers: The digital revolution," *Journal of Electronic Defense*, vol. 23, no. 6, pp. 45–45, 2000.

[3] ——, "Time of arrival emitter location," *Journal of Electronic Defense*, vol. 12, no. 6, pp. 80–81, 1995.

[4] ——, "Precise targeting: Sensors get smarter-the author of JED's monthly EW 101'column takes a look at efforts to improve sensors in order to get iron on target faster and more accurately." *Journal of Electronic Defense*, vol. 23, no. 9, pp. 51–56, 2000.

[5] J. Herskovits, "Feasible direction interior-point technique for nonlinear optimization," *Journal of optimization theory and applications*, vol. 99, no. 1, pp. 121–146, 1998.

[6] N. Cianos, "Low-cost, high-performance DF and intercept systems," in *Proceedings of WESCON'93*. IEEE, 1993, pp. 372–376.

[7] Z. Sun, Y. Zhou, and L. He, *Single and Multiple Station Active/Passive Positioning Technology*. Beijing: National Defense Industry Press, 1996, (in Chinese).

[8] Z. Sun and H. Chen, *Positioning, Navigation and Guidance*. Beijing: National Defense Industry Press, 1998, (in Chinese).

[9] G. Zhao, *Principles of Radar Countermeasures*. Xi'an: Xidian University Press, 1999, (in Chinese).

[10] Z. Guo, R. Sun, Y. Shen, and X. Jiang, "Covert communication in satellite-terrestrial systems via beamforming and jamming," *IEEE Transactions on Vehicular Technology*, pp. 1–16, 2025.

[11] U. I. Ahmed, T. ur Rehman, S. Baqar, I. Hussain, and M. Adnan, "Robust pulse repetition interval (PRI) classification scheme under complex multi emitter scenario," in *2018 22nd international microwave and radar conference (MIKON)*. IEEE, 2018, pp. 597–600.

[12] P. S. Ray, "A novel pulse TOA analysis technique for radar identification," *IEEE Transactions on Aerospace and Electronic systems*, vol. 34, no. 3, pp. 716–721, 2002.

[13] A. R. N. Nilchi and V. J. Mathews, "An efficient algorithm for joint estimation of differential time delays and frequency offsets," in *Proc. ICASSP*, vol. 5, 1992, pp. 309–312.

[14] S. Pandey and P. Agrawal, "A survey on localization techniques for wireless networks," *Journal of the Chinese Institute of Engineers*, vol. 29, no. 7, pp. 1125–1148, 2006.

[15] A. Yassin, Y. Nasser, M. Awad, A. Al-Dubai, R. Liu, C. Yuen, R. Raulefs, and E. Aboutanios, "Recent advances in indoor localization: A survey on theoretical approaches and applications," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 1327–1346, 2016.

[16] C. Laoudias, A. Moreira, S. Kim, S. Lee, L. Wirola, and C. Fischione, "A survey of enabling technologies for network localization, tracking, and navigation," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 3607–3644, 2018.

[17] N. Kubo, "Global navigation satellite system precise positioning technology," *IEICE Transactions on Communications*, 2024.

[18] F. S. Prol, R. M. Ferre, Z. Saleem, P. Välisuo, C. Pinell, E. S. Lohan, M. Elsanhoury, M. Elmusrati, S. Islam, K. Çelikbilek *et al.*, "Position, navigation, and timing (PNT) through low earth orbit (LEO) satellites: A survey on current status, challenges, and opportunities," *IEEE access*, vol. 10, pp. 83 971–84 002, 2022.

[19] H. Sallouha, S. Saleh, S. De Bast, Z. Cui, S. Pollin, and H. Wymeersch, "On the ground and in the sky: A tutorial on radio localization in ground-air-space networks," *IEEE Communications Surveys & Tutorials*, vol. 27, no. 1, pp. 218–258, 2024.

[20] Z. Shen, J. Li, and Q. Wu, "Data-driven interference localization using a single satellite based on received signal strength," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 8, pp. 8657–8669, 2020.

[21] D. K. Petraki, M. P. Anastasopoulos, T. Taleb, and A. V. Vasilakos, "Positioning in multibeam geostationary satellite networks," in *2009 IEEE International Conference on Communications*. IEEE, 2009, pp. 1–5.

[22] H. Dong, C. Yin, and Y. Zhang, "Research on RSS based multi station passive location method for satellite emitter," in *2022 IEEE 10th International Conference on Information, Communication and Networks (ICICN)*. IEEE, 2022, pp. 147–151.

[23] C. He, F. Guo, X. Li, and M. Zhang, "Bias analysis of AOA-Based Geolocation," in *2018 2nd IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*. IEEE, 2018, pp. 1711–1715.

[24] C. He, M. Zhang, and F. Guo, "Bias compensation for AOA-geolocation of known altitude target using single satellite," *IEEE Access*, vol. 7, pp. 54 295–54 304, 2019.

[25] J. Mason, "Algebraic two-satellite TOA/FOA position solution on an ellipsoidal Earth," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 40, no. 3, pp. 1087–1092, 2004.

[26] C. He, Y. Yuan, and B. Tan, "Alternating direction method of multipliers for TOA-based positioning under mixed sparse LOS/NLOS environments," *IEEE Access*, vol. 9, pp. 28 407–28 412, 2021.

[27] K. Ho and Y. Chan, "Solution and performance analysis of geolocation by TDOA," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 29, no. 4, pp. 1311–1322, 1993.

[28] W. W. Smith and P. G. Steffes, "Time delay techniques for satellite interference location system," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 25, no. 2, pp. 224–231, 2002.

[29] F. Shu, S. Yang, Y. Qin, and J. Li, "Approximate analytic quadratic-optimization solution for TDOA-based passive multi-satellite localization with earth constraint," *IEEE access*, vol. 4, pp. 9283–9292, 2016.

[30] K. Becker, "Three-dimensional target motion analysis using angle and frequency measurements," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, no. 1, pp. 284–301, 2005.

[31] B. Lee, Y. Chan, F. Chan, H.-J. Du, and F. A. Dilkes, "Doppler frequency geolocation of uncooperative radars," in *MILCOM 2007-IEEE Military Communications Conference*. IEEE, 2007, pp. 1–6.

[32] R. J. Webster, "An exact trajectory solution from Doppler shift measurements," *IEEE Transactions on Aerospace and Electronic systems*, no. 2, pp. 249–252, 1982.

[33] P. Ellis, D. Van Rheeden, and F. Dowla, "Use of Doppler and Doppler rate for RF geolocation using a single LEO satellite," *IEEE Access*, vol. 8, pp. 12 907–12 920, 2020.

[34] K. Ho and Y. Chan, "Geolocation of a known altitude object from TDOA and FDOA measurements," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 33, no. 3, pp. 770–783, 1997.

[35] P. Blanc-Benon and G. Bienvenu, "Passive target motion analysis using multipath differential time-delay and differential Doppler shifts," in *1995 International Conference on Acoustics, Speech, and Signal Processing*, vol. 5. IEEE, 1995, pp. 3139–3142.

[36] R. Ulman and E. Geraniotis, "Wideband TDOA/FDOA processing using summation of short-time CAF's," *IEEE transactions on signal processing*, vol. 47, no. 12, pp. 3193–3200, 2002.

[37] D. C. Shin and C. L. Nikias, "Complex ambiguity function based on fourth-order statistics for joint estimation of frequency-delay and time-delay of arrival," in *Proceedings of 27th Asilomar Conference on Signals, Systems and Computers*. IEEE, 1993, pp. 461–465.

[38] P. Liu, Z. Wu, Z. Yao, T. Wang, and M. Lu, "Robust single-point localization technique using downlink TDOA-AOA fusion," in *2024 14th International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2024, pp. 1–5.

[39] E. Widdison and D. G. Long, "A review of linear multilateration techniques and applications," *IEEE Access*, vol. 12, pp. 26 251–26 266, 2024.

[40] Y. Z. Bin, W. Lei, C. P. Qun, and L. A. Nan, "Passive satellite localization using TDOA/FDOA/AOA measurements," in *IEEE Conference Anthology*, 2013, pp. 1–5.

[41] Q. Jin, K. M. Wong, and Z.-Q. Luo, "The estimation of time delay and Doppler stretch of wideband signals," *IEEE Transactions on Signal Processing*, vol. 43, no. 4, pp. 904–916, 1995.

[42] L. G. Weiss, "Wavelets and wideband correlation processing," *IEEE signal processing magazine*, vol. 11, no. 1, pp. 13–32, 1994.

[43] M. Azaria and D. Hertz, "Time delay estimation by generalized cross correlation methods," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 32, no. 2, pp. 280–285, 1984.

[44] C. Knapp and G. Carter, "The generalized correlation method for estimation of time delay," *IEEE transactions on acoustics, speech, and signal processing*, vol. 24, no. 4, pp. 320–327, 2003.

[45] M. L. Fowler and X. Hu, "Signal models for TDOA/FDOA estimation," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 44, no. 4, pp. 1543–1550, 2009.

[46] S. Stein, "Algorithms for ambiguity function processing," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 29, no. 3, pp. 588–599, 2003.

[47] Y. Chan, K. Ho, and P. Ching, "Scaling and filtering of a sampled signal by the continuous wavelet transform," in *Proceedings of the IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis (Cat. No. 98TH8380)*. IEEE, 1998, pp. 345–348.

[48] R. K. Young, *Wavelet theory and its applications*. Springer Science & Business Media, 2012, vol. 189.

[49] X. Niu, P. Ching, and Y. Chan, "Wavelet based approach for joint time delay and Doppler stretch measurements," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 35, no. 3, pp. 1111–1119, 2002.

[50] K. Ho and Y. T. Chan, "Optimum discrete wavelet scaling and its application to delay and Doppler estimation," *IEEE Transactions on Signal Processing*, vol. 46, no. 9, pp. 2285–2290, 1998.

[51] Y.-T. Chan and K. Ho, "Joint time-scale and TDOA estimation: Analysis and fast approximation," *IEEE Transactions on Signal processing*, vol. 53, no. 8, pp. 2625–2634, 2005.

[52] M. R. Sharif and S. S. Abeysekera, "Efficient wideband signal parameter estimation using a radon-ambiguity transform slice," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 43, no. 2, pp. 673–688, 2007.

[53] H. M. Ozaktas, O. Arikan, M. A. Kutay, and G. Bozdagt, "Digital computation of the fractional Fourier transform," *IEEE Transactions on signal processing*, vol. 44, no. 9, pp. 2141–2150, 1996.

[54] A. Bultheel and H. E. M. Sulbaran, "Computation of the fractional Fourier transform," *Applied and Computational Harmonic Analysis*, vol. 16, no. 3, pp. 182–202, 2004.

[55] S.-C. Pei, W.-L. Hsue, and J.-J. Ding, "Discrete fractional fourier transform based on new nearly tridiagonal commuting matrices," *IEEE Transactions on Signal Processing*, vol. 54, no. 10, pp. 3815–3828, 2006.

[56] M.-H. Yeh and S.-C. Pei, "A method for the discrete fractional Fourier transform computation," *IEEE Transactions on Signal Processing*, vol. 51, no. 3, pp. 889–891, 2003.

[57] J. Xu, G. Liao, and H. C. So, "Space-time adaptive processing with vertical frequency diverse array for range-ambiguous clutter suppression," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 9, pp. 5352–5364, 2016.

[58] X. Zhang, D. Yao, Q. Yang, Y. Dong, and W. Deng, "Knowledge-based generalized side-lobe canceller for ionospheric clutter suppression in HFSWR," *Remote Sensing*, vol. 10, no. 1, p. 104, 2018.

[59] L. Piras and G. Giacinto, "Information fusion in content based image retrieval: A comprehensive overview," *Information Fusion*, vol. 37, pp. 50–60, 2017.

[60] D. Lappas, V. Argyriou, and D. Makris, "Fourier transformation autoencoders for anomaly detection," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 1475–1479.

[61] M. S. Fasihi and W. B. Mikhael, "Brain tumor grade classification using LSTM neural networks with domain pre-transforms," in *2021 IEEE International Midwest Symposium on Circuits and Systems (MWSCAS)*. IEEE, 2021, pp. 529–532.

[62] Z. Zhang, X. Wang, Y. Zou, and R. Zhang, "A low complexity algorithm for time-frequency joint estimation of CAF based on numerical fitting," in *2020 IEEE/CIC International Conference on Communications in China (ICCC Workshops)*. IEEE, 2020, pp. 214–218.

[63] C. Mensing and S. Plass, "Positioning algorithms for cellular networks using TDOA," in *2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings*, vol. 4. IEEE, 2006, pp. IV–IV.

[64] K. Yang, J. An, X. Bu, and G. Sun, "Constrained total least-squares location algorithm using time-difference-of-arrival measurements," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 3, pp. 1558–1562, 2009.

[65] H. T. FARD, M. Atashbar, Y. Norouzi, and F. H. KASHANI, "Multireference TDOA-based source localization," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 21, no. 7, pp. 1920–1929, 2013.

[66] J. Smith and J. Abel, "Closed-form least-squares source location estimation from range-difference measurements," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 35, no. 12, pp. 1661–1669, 2003.

[67] G. Wang and H. Chen, "An importance sampling method for TDOA-based source localization," *IEEE Transactions on Wireless Communications*, vol. 10, no. 5, pp. 1560–1568, 2011.

[68] M. Rosić, M. Simie, and P. Lukić, "TDOA approach for target localization based on improved genetic algorithm," in *2016 24th Telecommunications Forum (TELFOR)*. IEEE, 2016, pp. 1–4.

[69] Y. T. Chan and K. C. Ho, "A simple and efficient estimator for hyperbolic location," *IEEE transactions on signal processing*, vol. 42, no. 8, pp. 1905–1915, 1994.

[70] K. Yang, G. Wang, and Z.-Q. Luo, "Efficient convex relaxation methods for robust target localization by a sensor network using time differences of arrivals," *IEEE transactions on signal processing*, vol. 57, no. 7, pp. 2775–2784, 2009.

[71] E. Xu, Z. Ding, and S. Dasgupta, "Source localization in wireless sensor networks from signal time-of-arrival measurements," *IEEE Transactions on Signal Processing*, vol. 59, no. 6, pp. 2887–2897, 2011.

[72] K. W. K. Lui, F. K. W. Chan, and H.-C. So, "Semidefinite programming approach for range-difference based source localization," *IEEE Transactions on Signal Processing*, vol. 57, no. 4, pp. 1630–1633, 2008.

[73] G. Wang, Y. Li, and N. Ansari, "A semidefinite relaxation method for source localization using TDOA and FDOA measurements," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 2, pp. 853–862, 2012.

[74] Y. Zou, Q. Wan, and H. Liu, "Semidefinite programming for TDOA localization with locally synchronized anchor nodes," in *2018 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 2018, pp. 3524–3528.

[75] S. A. Kharidia, Q. Ye, S. Sampalli, J. Cheng, H. Du, and L. Wang, "Hill: A hybrid indoor localization scheme," in *2014 10th International Conference on Mobile Ad-hoc and Sensor Networks*. IEEE, 2014, pp. 201–206.

[76] A. Sikora and V. F. Groza, "Fields tests for ranging and localization with time-of-flight-measurements using chirp spread spectrum rf-devices," in *2007 IEEE Instrumentation & Measurement Technology Conference IMTC 2007*. IEEE, 2007, pp. 1–6.

[77] L. Zwirello, T. Schipper, M. Jalilvand, and T. Zwick, "Realization limits of impulse-based localization system for large-scale indoor applications," *IEEE Transactions on Instrumentation and Measurement*, vol. 64, no. 1, pp. 39–51, 2014.

[78] M. M. Dos Santos, G. G. De Giacomo, P. L. Drews, and S. S. Botelho, "Matching color aerial images and underwater sonar images using deep learning for underwater localization," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6365–6370, 2020.

[79] J. Liu, Y. Hu, H. Peng, and A. u. M. Zaki, "Data-driven method using dnn for PD location in substations," *IET Science, Measurement & Technology*, vol. 14, no. 3, pp. 314–321, 2020.

[80] H. Wu, Y. Cheng, and H. Wang, "Data-driven passive localization with non-cooperative radiation sources via mutually inverse networks," *IEEE Communications Letters*, vol. 24, no. 4, pp. 792–796, 2020.

[81] Y. Xue, W. Su, H. Wang, D. Yang, and Y. Jiang, "DeepTAL: Deep learning for TDOA-based asynchronous localization security with measurement error and missing data," *IEEE Access*, vol. 7, pp. 122 492–122 502, 2019.

[82] X. Ye and Y. Zhang, "Research on UWB positioning method based on deep learning," in *2020 5th International Conference on Mechanical, Control and Computer Engineering (ICMCCE)*. IEEE, 2020, pp. 1505–1508.

[83] C. Zhao and Y. Zhao, "One recurrent neural networks solution for passive localization," *Neural Processing Letters*, vol. 49, no. 2, pp. 787–796, 2019.

[84] S. Ge, K. Li, and S. N. B. M. Rum, "Deep learning approach in DOA estimation: A systematic literature review," *Mobile Information Systems*, vol. 2021, no. 1, p. 6392875, 2021.

[85] Y. Zhuang, X. Sun, Y. Li, J. Huai, L. Hua, X. Yang, X. Cao, P. Zhang, Y. Cao, L. Qi *et al.*, "Multi-sensor integrated navigation/positioning systems using data fusion: From analytics-based to learning-based approaches," *Information Fusion*, vol. 95, pp. 62–90, 2023.

[86] Z. Huang, G. Ye, P. Yang, and W. Yu, "Application of multi-sensor fusion localization algorithm based on recurrent neural networks," *Scientific reports*, vol. 15, no. 1, p. 8195, 2025.