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A Mini-Review on Pseudolite-Based User Positioning: Are Simpler Approaches Better?

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ABSTRACT Pseudolites (PLs) transmit Global Navigation Satellite System (GNSS)-like signals and provide effective solutions to replace or augment GNSS in environments where signals are denied or degraded. This review provides an overview of existing studies on PL-based user positioning, categorized into standalone methods and sensor fusion approaches. Further, it examines the algorithms, implementations, and performance of these approaches. Standalone PL and simple algorithms are popular and appear to outperform sensor fusion and more complex algorithms when considering positioning accuracy alone. However, this finding may be highly misleading, as simpler approaches also tend to use simpler evaluation scenarios. Studies that directly compare algorithms are scarce. This indicates the need for systematic benchmarking.

INDEX TERMS Navigation, positioning, pseudosatellite, pseudolite (PL), sensor fusion.

I. INTRODUCTION

Global Navigation Satellite Systems (GNSS), including GPS, Galileo, GLONASS, and BeiDou, are widely used for positioning and navigation. However, GNSS signals suffer from important limitations in environments with signal obstructions or unavailability, such as urban canyons or underground, indoor, tunnel, and space environments [1], [2], [3], [4], [5], [6] (Fig. 1). In addition, GNSS signals are sensitive to jamming and atmospheric interference, which can degrade positioning accuracy.

To overcome these challenges, pseudolites (PLs) have emerged as an alternative or augmentation to GNSS-based positioning. PLs are ground-based or airborne transmitters that emit GNSS-like signals to provide data for positioning in GNSS-degraded or -denied environments [7]. While Low Earth Orbit (LEO) satellite constellations are gaining popularity as space-based alternatives for GNSS augmentation, PLs offer greater flexibility and ease of implementation for meeting application -specific constraints. Moreover, PLs have the same fundamental observables as GNSS, such as pseudorange, carrier phase, and Doppler shift.

A multi-PL system can independently provide reliable positioning where GNSS signals are obstructed or absent, with applications from aerial and ground to maritime and space [4], [6], [8], [9], [10], [11], [12], [13].

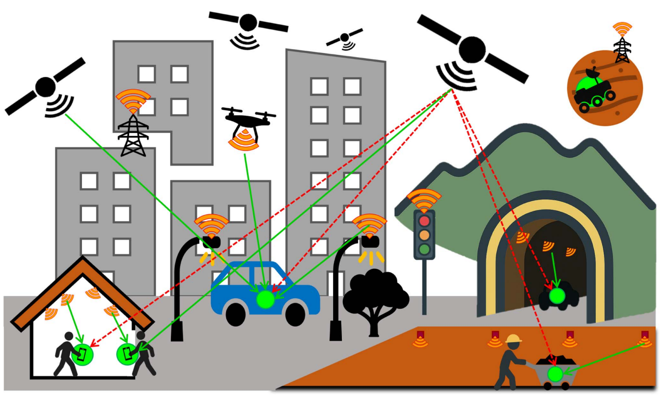

FIGURE 1. Overview of PL positioning in GNSS-obstructed and denied environments, including urban areas, indoors, tunnels, underground, and on Mars. Orange icons are PL transmitters, and green dots are receivers.

To enhance navigation accuracy, researchers have explored sensor fusion methods that integrate PLs with GNSS [14], [15], [16], inertial measurement units (IMUs) [17], [18], or laser ranging sensors [19], [20].

To the authors' best knowledge, there are only two review papers on PLs in positioning and navigation: In 2002, Wang [21] provided an early review of PL-based positioning, discussing hardware developments and various applications, particularly in PL-only systems and integration with GPS and Inertial Navigation Systems (INS). However, as an early study, it could only present simulation-based analyses and did not cover more recent advancements in real-world implementations and multisensor fusion techniques. In 2023, Liu et al. [7] provided a comprehensive review of PL technology in smart cities, addressing various applications and challenges. It explored the development history, system architecture, technical issues, and the potential role of PLs in enhancing smart city infrastructure. However, this system-level review focused on PLs in the context of smart cities, rather than on algorithmic details.

Since algorithms directly influence positioning accuracy and robustness, we aim to provide a structured overview of PL-based navigation by analyzing existing studies in terms of algorithms, implementations, and performance. The main contributions of this review are summarized as follows.

1) Existing PL-based user positioning studies are systematically categorized into standalone PL and sensor-fusion approaches.
2) A detailed comparison of the positioning algorithms, experimental environments, user types, and performance is presented.
3) Key literature gaps are identified, highlighting the lack of uniform benchmarking as a source of systematic accuracy biases across diverse experimental setups and test scenarios.

The rest of this article is organized as follows. Section II outlines the methodology for literature identification, screening, and selection. Section III summarizes the standalone PL-based positioning systems. Section IV covers sensor fusion with PLs, categorized into PL-GNSS, PL-IMU, and PL-Laser systems. Section V provides some analysis, future research directions, and limitations. Finally, Section VI concludes the article and presents the need for systematic benchmarking.

II. METHODOLOGY

The literature identification and selection process included the following steps: 1) searching studies in databases with keywords and removing duplicate studies; 2) screening titles and abstracts; 3) full-text reading and assessing eligibility based on the inclusion and exclusion criteria; and 4) final inclusion. The literature search was conducted on Google Scholar, IEEE Xplore, and Clarivate Web of Science using combinations of keywords including "pseudolite," "pseudo-satellite," "positioning," "navigation," and "sensor fusion" with Boolean operators. For example, Boolean queries included "pseudolite" AND ("positioning" OR "navigation"), "pseudolite" AND "sensor fusion." No publication year restrictions were applied. The final literature search was completed on 28 August 2025.

Inclusion criteria

1) Peer-reviewed journal or conference papers in English.
2) Studies that focus on user positioning with PLs.
3) Studies providing algorithmic and experimental positioning performance details.

Exclusion criteria

1) Studies not publicly accessible.
2) Studies focused on PL transmitter location determination, hardware development, or signal designs.
3) Studies from the same author group where multiple publications overlap, with a less methodological detailed version. If the details were comparable, the earlier paper was excluded.

Results reported under distinct experimental conditions in each study were analyzed separately, while results from different studies were analyzed separately when different algorithms or configurations were evaluated.

III. STANDALONE PSEUDOLITE-BASED NAVIGATION

Standalone PL navigation refers to positioning systems that rely solely on PLs without support from auxiliary sensors. It is particularly relevant in GNSS-denied or highly degraded environments, such as indoors, and has the advantage of flexibility and simplicity. Similar to GNSS, standalone PL requires a minimum of four PL signals to estimate the receiver's three-dimensional (3D) position and clock bias.

Based on the reviewed literature, 57% of included positioning studies use Least Squares (LS)-based approaches [10], [11], [12], [22], [23], [24], [25], [26], [27], [28], [29], [30], 24% apply Kalman Filter (KF) methods [31], [32], [33], [34], [35]. The remainder explores advanced approaches such as particle swarm optimization [36], projected cancellation [37], and deep-learning approaches [4], [38]. Pseudorange is the most common measurement type, and indoor tests dominate over outdoor and simulated cases. All the tests are conducted with multiple static PLs.

Both LS and KF approaches usually adopt the following pseudorange measurement model for the i-th PL transmitter $\hat{\rho}_i$:

$$\hat{\rho}_i = \left\| \mathbf{X}_u - \mathbf{X}_s^i \right\|_2 + c, \tag{1}$$

where $\mathbf{X}_u = (x_u, y_u, z_u)$ is the unknown user position, $\mathbf{X}_s^i = (x_{s_i}, y_{s_i}, z_{s_i})$ is the known position of the ith transmitter, and c is the user clock bias in length units.

Least Squares (LS) estimates the user state by minimizing the residuals between measured pseudorange ρ_i and modeled pseudoranges $\hat{\rho}_i$ over N received signals, similar to standard GNSS single point positioning (SPP)

$$(x_u, y_u, z_u, c) = \underset{(x_u, y_u, z_u, c)}{\text{argmin}} \sum_{i=1}^{N} (\hat{\rho}_i - \rho_i)^2 . \tag{2}$$

Kalman Filters (KF) and their variants, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), use constant-dynamics motion models in the prediction step [32], [33]. In the measurement step, some studies

TABLE 1. **Positioning Algorithms and Performance in Sensor Fusion With Pseudolites for Enhanced Navigation**

Sensors	Ref	Positioning Algorithm	Research Focus	Details and Performance
PL-GNSS	[14] (2021)	• Pseudorange LS • User position, clock bias	Seamless positioning for train transit at railway stations	• Simulated railway transit • Optimized PL layout/GPS alone achieved decimeter-/meter-level 3D accuracy.
	[15] (2022)	• Precise Point Positioning (PPP) • Tightly coupled EKF • 3D position, clock offsets, atmospheric errors, ambiguities	PL-augmented GNSS PPP for faster convergence time and improved accuracy.	• Outdoor pedestrian; cm-level accuracy; outperformed GNSS-only and PL-only.
	[16] (2012)	• Particle filtering (PF) • 2D position, velocity	Indoor-outdoor seamless pedestrian navigation with PL-GNSS integration.	• Real-world pedestrian; meter-level 2D accuracy; outperforming GPS alone. • Accuracy improved with floor plan constraints.
PL-IMU	[17] (2017)	• Loosely coupled EKF • User 2D position, 2D velocity, heading, three biases	PL and ultra-low-cost IMU integration with cycle slip detection for robust indoor positioning	• Indoor; rover; cm-level 2D accuracy • Improved PL-only accuracy by 30%.
	[18] (2017)	• Tightly coupled EKF • User 3D position, 3D velocity, orientation	PL-based positioning solution in Galileo test environment for automated vehicle navigation with industrial-grade MEMS IMU.	• 3D outdoor test; meter-level horizontal accuracy; outperformed LS-based methods. • Improved robustness in poor DOP conditions.
PL, IMU, Laser	[19] (2023)	• Weighted LS (WLS)	Fused PL, laser ranging, and digital elevation model (DEM) for 3D vehicle positioning in a highway tunnel.	• 4.6 km tunnel test; dm-level accuracy and precision.
PL, IMU, GNSS, Laser	[20] (2011)	• Tightly coupled EKF • User 3D position, 3D velocity, orientation	GPS, IMU, PL, and terrestrial laser scanning (TLS) integration for high-accuracy geolocation in unexploded ordnance detection.	• Outdoor; cm-level 2D accuracy • Proved PL and TLS helped maintain high accuracy in GNSS-denied environments.

utilize the pseudorange model in (1) [32], [33], or an extended version with double differencing [34], [35].

Appendix Table 4 presents a list of selected studies, highlighting their algorithms, research focus, and performance.

Although PL-unique issues like the near-far problem and cycle slips are primarily addressed through signal-level techniques, LS and KF-based approaches can mitigate their effects through measurement weighting or covariance adjustment.

IV. SENSOR FUSION WITH PSEUDOLITES FOR ENHANCED NAVIGATION

Sensor fusion can integrate the advantages of multiple sensor types and balance their weaknesses. Combining PL with complementary sensors mitigates its problems, such as multipath [39], [40], while also improving performance and robustness. Table 1 presents a list of PL sensor fusion studies, detailing the sensors used, positioning algorithms, research focus, and performance. Three sensor fusion groups were identified in the reviewed studies, namely PL-GNSS, PL-IMU, and PL-Laser:

1) *PL-GNSS Integration:* PLs usually transmit the same data type as GNSS, allowing their measurements to be used equivalently within positioning algorithms. For example, LS can jointly process PL and GNSS observations [14], and Precise Point Positioning (PPP) treats both in the same manner [41], [42]. Due to this advantage, PL-GNSS fusion supports seamless indoor-outdoor transition and maintains accuracy in GNSS-unstable environments. Studies further show it outperforms GNSS and PL alone [14], [15], [16].
2) *PL-IMU Integration:* PL-IMU integration can provide accurate navigation in GNSS-denied areas, such as indoors, where the IMU offers continuous and high-frequency motion updates and PL corrects accumulated drift. In the loosely and tightly coupled EKF for PL-IMU integration [17], [18], IMU data is used in the prediction step, and the PL observations refine the position estimate in the update step. Among the two studies, [17] employs an ultra-low-cost IMU, whereas [18] uses an industrial-grade MEMS IMU, leading to different drift correction roles of PL updates. Overall, PL-IMU fusion shows improved performance compared to PL-only navigation.
3) *PL-Laser Integration:* Laser sensors can effectively capture short-range environment data, particularly in enclosed or dense environments such as tunnels [19] or forests [20]. Studies demonstrate the benefits of PL and laser sensors in GNSS-obstructed environments [19], [20].

TABLE 2. **Summary of Experimental Environments, Positioning Dimensions, and User Types**

Env.	Dim.	Static User	Dynamic User
Simulation	2D	[23]	[23], [31], [37]
	3D	[22], [23]	**[43]**
Indoor	2D	[25]–[27], [30]	[24]–[26], [28], [33], [36], **[17]**
	3D	[34], [35]	[10], [32], [34], [35]
Outdoor	2D	[27]	[11], [27], [29], [37], [38]
	3D	–	**[15], [18], [20]**

Bold References Denote Sensor Fusion Approaches, While Regular Font Indicates Standalone PL Studies.

Based on Table 1, three studies employ tightly coupled EKF, one adopts a loosely coupled EKF, two use LS-based methods, and one implements a particle filter. There is no clear conclusion on the most effective integration due to varying applications and setups. Moreover, factor-graph approaches, popular methods in navigation, have not yet been explored for PL positioning. Since PL shares the same measurements as GNSS, the factor graph framework developed for GNSS can be directly extended to PL fusion.

Both GNSS and IMU are common choices, appearing in four of the seven reviewed papers, with PL-IMU-EKF being the dominant sensor-algorithm combination (three of seven). Overall, integrating complementary sensors with PL can improve the positioning accuracy and robustness.

V. DISCUSSION

Table 2 summarizes the experimental setups by environment, dimension, and user type, while Table 3 summarizes

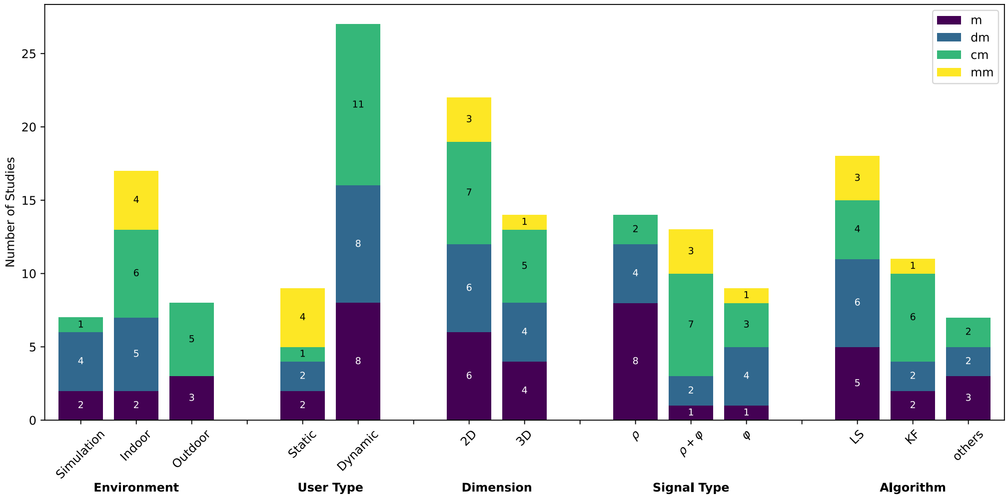

FIGURE 2. **Positioning accuracy distribution across different configurations. The variable ρ is pseudorange, and φ represents carrier phase and/or Doppler.**

TABLE 3. **Summary of Signal Types, Positioning Algorithms, and Achieved Accuracy Levels**

Signal Type	Alg.		References and Accuracy Level
Pseudorange	LS	*Static*:	[22] (m), [23] (m, 3D), [23] (cm, 2D)
		Dynamic:	[12] (m), [23] (dm), **[43]** (dm)
	KF	*Static*:	–
		Dynamic:	[33] (m), **[18]** (m), [31] (dm)
	Others	*Static*:	–
		Dynamic:	**[16]** (m), [4] (m), [37] (m, outdoor), [37] (dm, simulation), [38] (cm)
Pseudorange + Carrier Phase	LS	*Static*:	[27] (mm), [30] (mm)
		Dynamic:	[11] (m), **[19]** (dm), [24] (cm), [27] (cm)
	KF	*Static*:	[34] (dm), [35] (mm)
		Dynamic:	[35] (cm), [34] (cm), **[15]** (cm), **[20]** (cm)
	Others	*Static*:	–
		Dynamic:	[36] (cm)
Carrier Phase / Doppler	LS	*Static*:	[26] (dm), [25] (mm)
		Dynamic:	[26] (dm) (m), [28] (dm), [25] (dm), [10] (dm), [29] (cm)
	KF	*Static*:	–
		Dynamic:	[32] (cm), **[17]** (cm)

Bold References Denote Sensor Fusion Approaches, While Regular Font Indicates Standalone PL Studies.

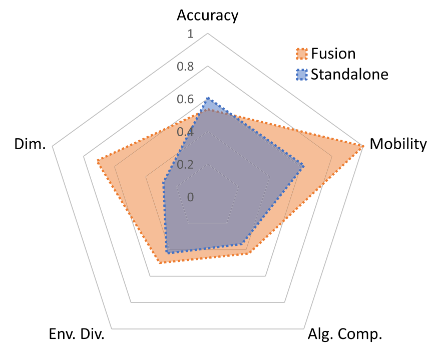

FIGURE 3. **Radar plot for standalone PL and sensor fusion comparison. The weighted scores on each axis, where larger values represent more favorable relative characteristics, are: Accuracy (0.25 for m, 0.5 for dm, 0.75 for cm, 1.0 for mm); Mobility (0 for static, 1 for dynamic); Algorithm Complexity (0 for LS, 0.5 for KF, 1 for others); Environment Diversity (0 for simulation, 0.5 for indoor, 1 for outdoor); and Dimensionality (0 for 2D, 1 for 3D). The selected weights are illustrative, and the qualitative interpretations remain stable under alternative reasonable choices. Values shown are weighted averages across studies for all indicators, so radar-axis values are continuous rather than discrete.**

signal types, algorithms, and accuracy for both standalone and sensor fusion systems. Figs. 2 and 3 visualize these results, showing accuracy distributions across configurations and comparing standalone with sensor fusion. Note that reported accuracy metrics vary across studies (e.g., 2D versus 3D, mean versus root mean square), and were therefore categorized into broad accuracy levels (mm/cm/dm/m) without recomputing or normalizing the original statistics.

A. ENVIRONMENT AND USER TYPE

Table 2 shows that all sensor fusion studies are conducted with dynamic users, mostly in outdoor 3D environments. This reflects the needs of vehicle and pedestrian navigation, where motion can introduce challenges, and outdoor conditions require higher robustness. In addition to the scenarios in Table 2, some special cases include underwater [12], tunnels [4], [19], and indoor-outdoor seamless transition [16].

In contrast, static users are primarily associated with standalone PL setups, often limited to simulation or indoor environments as proofs of concept. Notably, no static user has been tested in outdoor 3D settings, and few studies address indoor 3D cases. Indoor applications such as pedestrians [25], [27], railway vehicles [24], [27], and wheeled rovers [28], [36] typically operate on planar surfaces, where altitude information is less meaningful. Static users in the outdoors offer limited practical value.

Overall, standalone PL navigation appears suitable for simple and static environments, while sensor fusion methods are preferred in more complex and dynamic scenarios. These observations are supported by Fig. 3 in terms of mobility, environment diversity, and dimensionality.

B. ALGORITHMS, SIGNALS, AND PERFORMANCE

Table 3 and Fig. 2 show that LS is the most widely used algorithm. Although KF and more advanced algorithms are theoretically expected to offer higher performance, some of the best results were still achieved with LS (Fig. 2 Algorithm Group). This is because LS was often applied in simple and static user setups, reflecting its suitability for systems with slow dynamics. However, only [18] and [38] compared their methods with LS, demonstrating that EKF and neural network-based approaches outperform LS in the same scenario. Notably, the "Others" algorithm group, which includes neural network-based approaches, is based on a limited number of studies compared to the LS and KF groups, limiting how its performance can be interpreted.

Fig. 3 shows that fusion-based approaches have higher complexity and variety than standalone PL systems. By incorporating complementary sensors, fusion-based systems are anticipated to improve performance. For PL-GNSS, direct comparisons confirm improvement over standalone PL, but there is no such benchmarking for PL-IMU and PL-Laser. Nevertheless, when averaging across studies, PL standalone systems appear to score slightly better in accuracy (Fig. 3), mainly because they are tested in simpler setups or indoor environments.

Systems using carrier-phase measurements, either alone or combined with pseudorange, generally offer better positioning accuracy than pseudorange-only studies (Fig. 2 Signal Type Group), which aligns with theoretical expectations.

All four of the most accurate results at the millimeter level were achieved for static users in indoor environments, with three of the four being 2D cases using LS (Fig. 2 Algorithm Group). These results support the observation that higher accuracies are associated with simple experimental setups. However, across the reviewed studies, there is no clear evidence on which algorithms and signals provide better performance. Among the four mm-level studies, one uses a common-clock architecture, one employs wireless synchronization, and two do not report synchronization details, making it difficult to observe the effects of synchronization quality on performance.

Results shown in Table 3 and Fig. 2 can only serve as indications, as positioning accuracy depends on various factors, including test environments, sensor quality configurations, algorithm configuration, and hardware characteristics. Across the reviewed studies, PL transmitters were implemented on diverse hardware platforms, such as software-defined radios and commercial GNSS signal generators with varying performance grades. However, detailed transmitter specifications were not consistently reported, limiting hardware-based comparisons and cross-study performance interpretation.

C. CHALLENGES AND FUTURE WORK

Several open challenges and opportunities for future research remain in the development of PL navigation systems.

1) *Extended Sensor Integration:* While current PL fusion studies focus on GNSS, IMUs, and laser ranging devices, future work may explore integration with Wi-Fi, Bluetooth, vision, or LiDAR sensors, particularly within factor graph frameworks, for environments where GNSS signals are absent or degraded.
2) *Multipath and Challenging Conditions:* Multipath effects in PL navigation systems are theoretically more severe than GNSS due to transmitter proximity and higher signal power. Existing mitigation methods have been evaluated only indoors or in simulations [28], [39], [40], [44], while outdoor and mixed environments remain insufficiently studied. Moreover, most high-accuracy results are reported under static or indoor conditions. Future studies should therefore emphasize more challenging scenarios, such as severe multipath, unstable PL signals, high-dynamic motion, and crowded environments with dynamic obstructions.
3) *Dynamic PL Deployment:* Most existing PL systems rely on static transmitters, limiting their effectiveness and applicability in dynamic or complex environments. Recent studies have utilized unmanned aerial vehicles as dynamic PLs to enable flexible and adaptive geometries [8], [9], [45], demonstrating potential benefits in coverage and geometric strength. However, these studies focus only on PL deployment and configuration, without evaluating user positioning performance. Future work should investigate dynamic PL for real-time user positioning.

D. LIMITATIONS

The literature search was conducted only in Google Scholar, IEEE Xplore, and Clarivate Web of Science, which may have missed relevant studies in other databases. No second reviewer independently validated inclusion and exclusion decisions, which may introduce bias.

VI. CONCLUSION

PL-based positioning shows potential as both a replacement and an augment for GNSS, but its performance depends strongly on algorithm and implementation settings. Despite theoretical expectations favoring advanced algorithms and fusion strategies, this review found that some of the highest reported accuracies were achieved by simple LS-based standalone systems, while advanced algorithms and fusion strategies did not consistently show superior results. This outcome reflects the lack of fair benchmarking, as simpler approaches were often tested indoors and on static users, whereas more advanced methods were evaluated under more challenging conditions. Establishing open-access benchmark datasets across diverse environments is a vital next step for the PL research community to enable reproducible and standardized evaluation.

APPENDIX

Table 4 lists standalone PL studies, grouped by algorithm, supporting Sections III.

TABLE 4. Positioning Algorithms and Performance in Standalone PL Navigation

Ref	Positioning Algorithm	Research Focus	Details and Performance
		LS-based methods	
[22] (2014)	• Pseudorange LS • User 3D position, clock bias	PL system transmitting GPS-like signals, allowing unmodified GPS receivers to process them.	• Simulation; meter-level 3D accuracy; static user.
[23] (2015)	• Pseudorange LS • User position, clock bias	PL-based indoor positioning system by relaying real GPS signals from outdoor receivers to indoor transmitters.	• 2D and 3D static simulations; horizontally/vertically achieve cm/meter-level accuracy. • 2D dynamic simulation, accuracy degrades by one order.
[11] (2018)	• Pseudorange LS • Ferry 2D position, heading	Virtual receiver for enhancing ferry availability, reliability, and precision in a PL-equipped harbor.	• Dynamic ferry; solution availability +20%; Precision +10% (up to 50% in harbor).
[12] (2020)	• Pseudorange weighted LS • 3D underwater user position	Underwater positioning using buoy-based pseudolites and custom electromagnetic signals for vehicles/divers.	• Real-world experiments; depth of 30 m underwater; accuracy $<$ 3 meters.
[24] (2018)	• Iterative LS (ILS) • Double difference (DD) pseudorange	Indoor positioning without point initialization.	• Indoor; cm-level 2D accuracy; dynamic experiment.
[25] (2019), [26] (2024), [10] (2024)	• Doppler differential LS velocity estimation • Linear position propagation	Indoor positioning approaches	• [25]: More precise than standard Doppler LS [39]; indoor; static/dynamic: mm-level/dm-level 2D accuracy. • [26]: Indoor; static/dynamic test: dm-level/meter-level 2D accuracy. • [10]: Indoor pedestrian scenario: dm-level 3D accuracy.
[27] (2003)	• Carrier phase LS • User 2D position, clock bias	PL transceiver "Locatalite" transmits GPS-like signals time-synchronized within picoseconds.	• Indoor, outdoor; mm-level 2D precision; static case. • Outdoor; cm-level 2D precision; dynamic cases.
[28] (2023)	• Carrier phase LS • User 2D position • Extension of [46]	Shallow neural networks and transfer learning-based deep neural networks for indoor multipath detection to enhance positioning.	• Indoor rover; dm-level 2D accuracy. • Positioning errors reduced by 10% with proposed multipath detection.
[29] (2001)	• Carrier phase Quadratic Iterated LS (QILS) • Rover 2D position	Self-Calibrating PL Array (SCPA) for accurate, drift-free Mars rover localization.	• Outdoor; cm-level; drift-free localization; Mars rovers.
[30] (2020)	• DD carrier phase LS	Hardware and software methods to correct time and frequency deviations between the user, reference receivers, and PLs.	• Hardware method; 2D deviation $<$ 7 mm. • Software method; mm-level accuracy after the initialization phase.
		KF-based methods	
[31] (2022)	• Pseudorange EKF • User 2D position, velocity	EKF algorithm to improve indoor positioning accuracy.	• Simulated 2D indoor scenario; dm-level accuracy.
[32] (2016)	• Carrier phase EKF • User 3D position, orientation, ambiguity	Combined Doppler and carrier phase positioning to resolve carrier ambiguity and improve accuracy.	• After convergence, cm-level accuracy and precision. • Outperformed Doppler positioning.
[33] (2010)	• EKF-based vector tracking loop (VTL) • Pseudorange, Doppler	VTL algorithm to improve positioning availability and mitigate the near-far problem.	• Improved positioning availability; meter-level accuracy; indoor simulated 2D train-on-track scenario.
[34] (2019), [35] (2019)	• [34]: Unscented KF (UKF) • [35]: Robust UKF (RUKF) • Pseudorange, carrier phase • User 3D position, ambiguity	Differential PL and RTK-based indoor positioning using UKF, further enhanced with a RUKF and partial ambiguity resolution.	• Indoor static/dynamic tests: UKF achieved dm/cm-level, RUKF mm/cm-level accuracy. • Performance ranking: RUKF, UKF, EKF.
		Advanced methods	
[36] (2022)	• Adaptive particle swarm optimization for initial estimate • LS for refinement • Pseudorange, carrier phase	Adaptive on-the-fly method to eliminate ambiguity and improve positioning precision.	• Indoor; cm-level 2D accuracy; rover.
[37] (2022)	• Projected cancellation with ILS or Levenberg–Marquardt (LM) • Pseudorange	Projected cancellation to linearize pseudoranges at a virtual site, with ILS for weak nonlinearity, or with LM for severe nonlinearity.	• 2D positioning accuracy: +23% (simulation), +17% (outdoor test), compared to LM. • Computation time -70% (simulation), -85% (outdoor test), compared to LM.
[38] (2022)	• Residual fully connected neural network (ResFCNN) • Pseudorange	Deep learning approach to improve positioning and mitigate multipath effects.	• Outdoor; 2D toy train user; ResFCNN/ILS: cm-level/meter-level accuracy and precision.
[4] (2025)	• Enconv1d model based on the spatio-temporal features • Pseudorange	Deep learning-based algorithm for long-tunnel positioning and addressing signal degradation.	• 4.6 km tunnel real-world; meter-level accuracy.

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