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HYBRID BLE–PDR LOCALIZATION SYSTEM FOR SMART RETAIL ENVIRONMENTS

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ABSTRACT

Accurate indoor user localization is a key component in the development of cashier-free smart stores, enabling advanced customer experiences, security monitoring, and behavioral flow analysis. This paper presents a hybrid localization approach that combines inertial motion tracking (Pedestrian Dead Reckoning – PDR) with Bluetooth Low Energy (BLE) tag signals. Unlike systems that require dedicated infrastructure, the proposed solution uses existing BLE electronic shelf labels (ESLs) as reference points. Their identification signals are used to correct the PDR drift, thereby reducing the cumulative error typical of purely inertial methods. The mobile application continuously measures the Received Signal Strength Indicator (RSSI) from BLE tags and applies threshold-based position corrections, while the PDR module, based on the Scarlett step-length model, maintains continuous tracking between tags. The system additionally integrates map-based spatial constraints that eliminate physically impossible paths through a particle-filter mechanism. Experimental evaluation in a retail environment demonstrated an average error of 0.4 m for linear movement and 1.3 m for a complex circular trajectory, confirming meter-level localization accuracy without the need for cloud processing. All computations are performed locally on the user's device, ensuring privacy protection and enabling real-time movement analysis and context-aware retail interaction.

Keywords: BLE tags, Indoor localization, PDR, IMU sensors, Map constraints, Smart retail, IoT in retail.

INTRODUCTION

With the rapid advancement of smart retail technologies and the emergence of cashier-free store concepts, accurate indoor user tracking has become a key factor in enhancing the functionality, efficiency, and security of retail systems. Real-time customer localization enables a range of advanced features, including product navigation, personalized offers, movement-flow analysis, and shelf-layout optimization. Beyond commercial benefits, indoor positioning systems (IPS) also have important safety applications, enabling the detection of unusual movement patterns and workspace monitoring without the need for video surveillance.

Traditional IPS solutions rely on visual tracking systems, Wi-Fi infrastructure, Ultra-Wideband (UWB) sensors, or their combinations. Although these systems can achieve high accuracy, their deployment in real retail environments requires expensive equipment, complex installation, and often raises privacy concerns. In contrast, Bluetooth Low Energy (BLE) technology offers an economical and technically simple alternative. BLE beacons periodically emit low-power identification signals that enable indoor positioning without centralized data processing. Their low cost, energy efficiency, and broad compatibility with modern smartphones make them suitable for large-scale implementation. However, BLE-based approaches suffer from Received Signal Strength Indicator (RSSI) variability caused by reflections and obstacles, which affects positioning accuracy and consistency.

Smartphone inertial sensors — accelerometer, gyroscope, and magnetometer enable continuous relative motion tracking through Pedestrian Dead Reckoning (PDR) algorithms. While PDR ensures smooth tracking continuity, it is prone to cumulative error due to sensor drift. Therefore, modern research focuses on data fusion of BLE and inertial measurements, where BLE provides absolute reference points, and PDR maintains motion continuity between them.

This study explores the integration of existing BLE infrastructure, in the form of Electronic Shelf Labels (ESLs), with smartphone inertial sensors to achieve accurate, locally processed, and privacy-preserving indoor user localization in retail spaces. By combining BLE RSSI corrections, a Scarlett-model-based PDR algorithm, and map-based spatial constraints, the system achieves meter-level localization accuracy without additional infrastructure or cloud processing.

OVERVIEW OF EXISTING INDOOR LOCALIZATION APPROACHES

Indoor localization represents a multilayered challenge since GNSS/GPS signals cannot reliably penetrate buildings (Zafari et al., 2019). Consequently, a variety of alternative

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methods have been developed, based on radio-frequency communication, motion sensors, visual systems, or environmental markers. Each technology has its own advantages and limitations in terms of accuracy, cost, infrastructure requirements, and privacy protection (Faragher & Harle, 2015; Liu et al., 2007) (see Table 1).

Table 1. Comparison of indoor localization technologies according to key parameters.

Technology	Accuracy	Cost	Infrastructure	Battery life	Privacy
BLE tags	1–2 m	Low	Existing ESL infrastructure	Long	High
Wi-Fi RTT	1–3 m	Medium	Wi-Fi routers	Moderate	Low
UWB	< 0.5 m	High	Dedicated transmitters	Short	Medium
PDR	Error increases over time	Low	None	N/A	High

Wi-Fi Localization

Wi-Fi networks are widely used since they are already deployed in most buildings. The two dominant methods are trilateration, which estimates distance based on signal strength from multiple access points, and fingerprinting, which relies on pre-mapped RSSI patterns in space (Liu et al., 2007; Bahl & Padmanabhan, 2000). Although these systems provide acceptable accuracy, their performance often degrades due to multipath reflections, environmental changes, and the need for frequent remapping, which limits long-term reliability (Xiao et al., 2016).

Ultra-Wideband (UWB)

UWB technology achieves centimeter-level accuracy by measuring Time-of-Arrival (ToA) of radio signals (Li et al., 2018). However, it requires dedicated hardware and anchor receivers, while most smartphones still lack native UWB support (Ho et al., 2016). Due to high deployment costs and limited availability, UWB is mainly applied in industrial and logistics environments where precise spatial analysis is essential (Vezočnik & Jurič, 2022).

Vision-Based Systems

Camera-based systems, such as those used in Amazon Go stores, enable highly accurate real-time user tracking but require extensive image processing, storage capacity, and computational resources (Harder et al., 2022). Moreover, they pose significant challenges related to data privacy and personal information protection (Milano et al., 2024), which restricts their adoption in smaller or open retail settings.

Bluetooth Low Energy (BLE)

BLE technology provides a practical trade-off between accuracy, energy efficiency, and cost. BLE beacons periodically emit low-power identification signals that allow positioning without the need for centralized servers (Faragher & Harle, 2015; Naser et al., 2023).

The three most common BLE localization methods are:

1. Trilateration – estimating position based on distances from multiple tags;
2. Fingerprinting – mapping of RSSI values throughout the area;
3. Proximity – selecting the nearest tag based on signal strength.

Although trilateration theoretically offers higher precision, in real environments BLE signals fluctuate due to reflections and obstructions (Li et al., 2018). Consequently, proximity-based localization proves more stable and suitable for dynamic retail environments.

Pedestrian Dead Reckoning (PDR)

PDR methods use a smartphone's accelerometer, gyroscope, and magnetometer to detect user steps, orientation, and step length (Ho et al., 2016; Vezočnik & Jurič, 2022). They provide continuous tracking even without external signals but are susceptible to cumulative drift, especially during longer paths or turns (Ashraf et al., 2023). Adaptive step-length models and fusion with BLE signals can significantly mitigate this drift and improve stability (Fox et al., 1999).

Fusion of BLE and PDR with Map Constraints

Modern indoor localization systems frequently combine BLE and inertial data to increase robustness and accuracy (Harder et al., 2022; Ascher et al., 2012). BLE supplies absolute reference points, while PDR maintains movement continuity between them. When combined with a map of the physical environment (walls, shelves, corridors), a particle-filter algorithm estimates the most probable user position and eliminates physically impossible trajectories (Szyc et al., 2023). This integrated approach achieves meter-level accuracy, ensures local data processing, and maintains a high level of privacy, making it well suited for deployment in smart retail environments.

SYSTEM ARCHITECTURE AND METHODOLOGY

Overall System View

The proposed system consists of a network of Bluetooth Low Energy (BLE) tags (Electronic Shelf Labels – ESL) deployed throughout the store and a mobile application utilizing smartphone sensors. BLE tags periodically broadcast short-range identification packets, while the application performs passive scanning and measures the corresponding Received Signal Strength Indicator (RSSI) values. Simultaneously, the smartphone's Inertial Measurement Unit (IMU) composed of the accelerometer, gyroscope, and magnetometer is used for Pedestrian Dead Reckoning (PDR), ensuring continuous tracking between absolute BLE "anchors" (Faragher & Harle, 2015; Li et al., 2018; Naser et al., 2023). By integrating map constraints that define corridors, walls, and passageways, the system eliminates physically impossible trajectories (Harder et al., 2022; Ascher et al., 2012; Szyc et al., 2023). A conceptual overview of the data layers and processing flow is presented in Figure 1. and Figure 2.

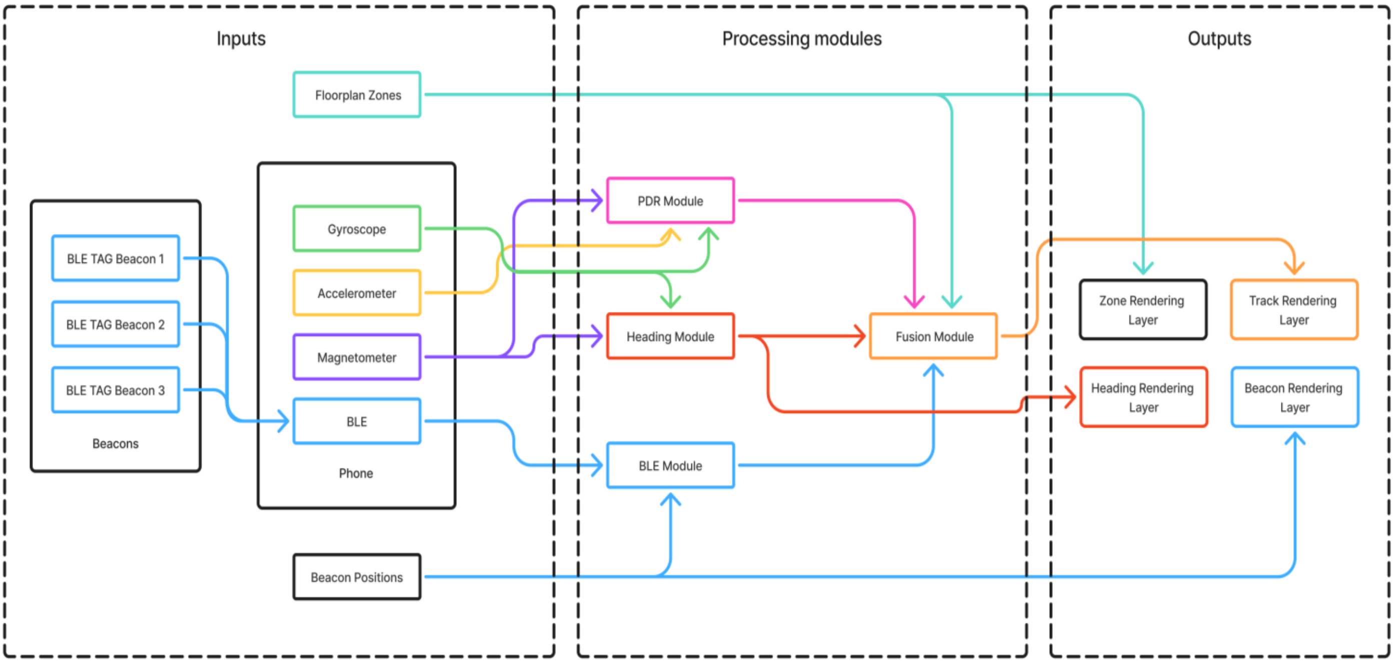

Figure 1. System architecture (BLE ESL tags – smartphone sensors – on-device fusion and UI).

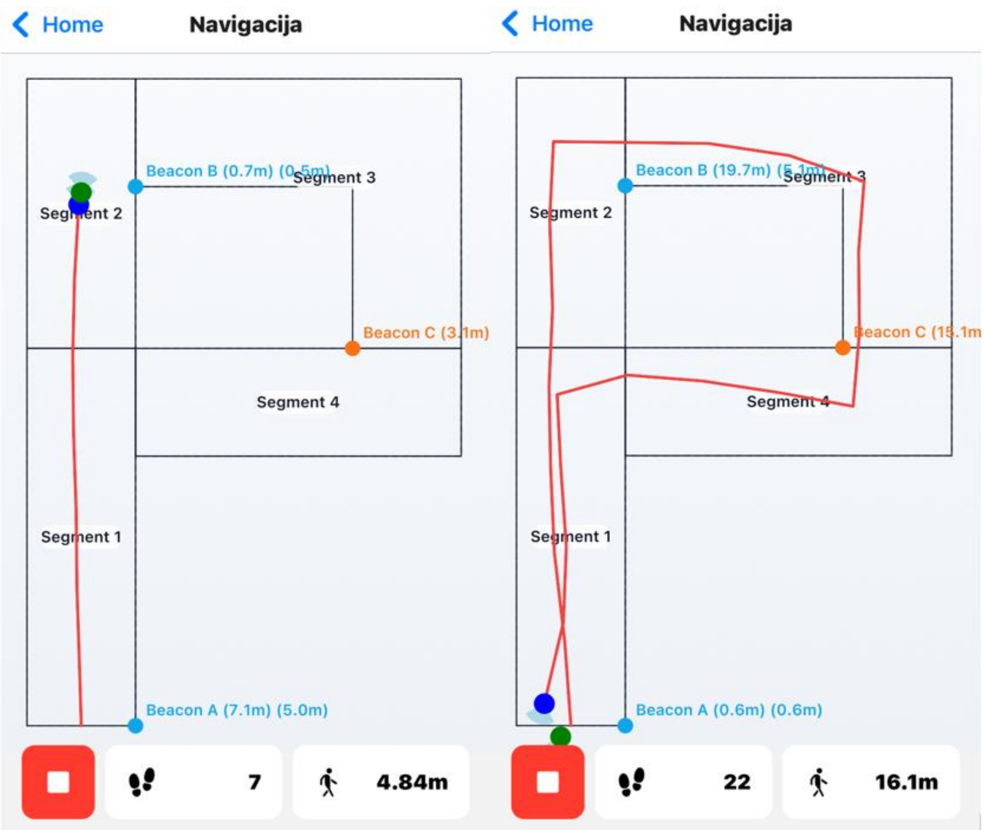

Figure 2. Visualization of user trajectory during indoor tests without PDR path centering (blue: PDR; green: BLE proximity fix).

Scarlett-Type PDR with Dynamic Step Length

The PDR module detects steps from the vertical acceleration component and estimates the user's heading by combining gyroscope data (short-term stability but prone to drift) and magnetometer readings (long-term reference but noise-sensitive) using a complementary filter (Ho, Truong & Jeong, 2016), (Vezočnik & Jurič, 2022).

A dynamic step-length model (Scarlett-type) is applied, in which the step length is calculated from the statistical features of the acceleration signal during each step:

$$L = \alpha(\alpha_{\max} - \alpha_{\min}) + \beta(\mu - g) + \gamma MAD. \quad (1)$$

where $\alpha_{\max}$ and $\alpha_{\max}$ are the maximum and minimum accelerations within a step, μ is the mean acceleration, g=9.80665 m/s2 represents gravity, and *MAD* is the mean absolute deviation. Empirically calibrated coefficients are α=−0.15615, β=−0.06246, and γ=2.4015.

Step detection is based on thresholding negative acceleration peaks with temporal constraints to prevent false detections.

- Typical sampling and filtering parameters are: sampleHz = 150 Hz, gravityCutoffHz = 0.8 Hz, warmupMs = 400 ms,
- minStepIntervalMs = 500 ms, maxStepIntervalMs = 2000 ms, peakThreshold = 0.3 g, maxSamplesPerStep = 400.

This approach is computationally lightweight and well suited for real-time on-device processing (Ho et al., 2016; Vezočnik & Jurič, 2022; Ashraf et al., 2023).

BLE Proximity for Drift Reset and Correction

Instead of relying on BLE trilateration which is often unstable indoors due to multipath effects and RSSI fluctuations the system employs proximity and weighted-centroid correction.

When the measured RSSI exceeds a defined threshold (e.g., > −65 dBm), indicating proximity to a specific ESL tag, the current PDR position is anchored to the known coordinates of that tag, effectively resetting cumulative drift (Faragher & Harle, 2015; Li et al., 2018; Milano et al., 2024; Naser et al., 2023).

If multiple tags are simultaneously detected, the user's position can be computed as a weighted centroid, where the weights are inversely proportional to the estimated distances from each tag, producing a more robust estimation under noisy conditions (Faragher & Harle, 2015; Li et al., 2018).

Map Constraints and Aisle Alignment

A pre-defined floor plan, including walls, shelves, and walkways, is used as a map constraint layer. The algorithm rejects or adjusts position estimates that fall outside walkable zones by projecting the location to the nearest valid area, typically the center axis of an aisle.

This "line-snapping" approach ensures visual stability and realistic trajectory alignment. Such map-aided localization methods have been shown to significantly reduce drift and improve PDR trajectory stability, especially over extended or complex paths (Harder et al., 2022; Ascher et al., 2012; Szyc et al., 2023).

Implementation Notes

BLE packet scanning is performed periodically (batched mode) with median or Kalman filtering applied to the RSSI data. The PDR computation loop runs at the IMU sampling frequency, while map corrections are applied after each detected step or BLE event.

All data processing and visualization are executed locally on the smartphone, without cloud-based computation, minimizing latency and ensuring user privacy.

The overall system architecture and methodology align with current best practices in BLE-based indoor localization and map-aided data fusion (Faragher & Harle, 2015; Li et al., 2018; Harder et al., 2022; Milano et al., 2024; Naser et al., 2023; Ascher et al., 2012; Szyc et al., 2023).

EXPERIMENTAL ENVIRONMENT AND EVALUATION

Environment Description and Protocol

The experimental evaluation was conducted in a controlled indoor area measuring 6 m × 4 m. BLE ESL tags were mounted on walls and shelves at a height of approximately 1 m.

The smartphone running the localization application was held in the user's hand, simulating realistic retail usage conditions.

The IMU sensors (accelerometer, gyroscope, magnetometer) were sampled at 150 Hz, while BLE scanning was performed in batched mode several times per second, using median or Kalman filtering for RSSI stabilization.

All data were logged on-device in real time. Figure 2 shows a representative user trajectory and the corresponding BLE correction points.

Two movement configurations were examined, covering both linear and curved motion patterns typical of retail aisle navigation:

- Linear motion: straight-line walking between two reference points spaced 6 m apart.
- Circular (P-shaped) motion: a predefined *P-shaped* path of approximately 16.7 m in total length.

The evaluation aimed to assess the accuracy of the Scarlett-type PDR combined with BLE proximity corrections and to examine the reliability of segment recognition based on RSSI distribution.

Linear Motion

The linear movement experiment was repeated 10 times, with an average of 7–8 steps per pass. The mean traveled distance was 5.61 m, yielding a root mean square error (RMSE) of 0.38 m. The largest deviations occurred during the initial and final steps, where variations in walking speed affected acceleration amplitude and step-length estimation. Under linear conditions, the Scarlett-based PDR demonstrated stable tracking with an error below 0.5 m, which satisfies aisle-level navigation accuracy.

Circular ("P-shaped") Motion

For the 16.71 m P-shaped path, ten repetitions were conducted, with 20–23 detected steps depending on the walking rhythm during turns. The calculated RMSE was 1.28 m. The main sources of error were heading drift during turns, step-length variation, and limited BLE correction selectivity in zones where multiple tags overlapped. Despite these effects, trajectory continuity was maintained, and map constraints successfully prevented unrealistic movement through walls, providing stable path visualization (Table 2.).

Table 2. Accuracy results for linear and P-shaped trajectories.

Scenario	Path length (m)	Repetitions	Average error (RMSE, m)
Linear	5.6	10	0.38
Circular (P)	16.7	10	1.28

Supplementary Statistical Analysis

To provide a more comprehensive insight into localization performance, additional statistical indicators were calculated for both motion scenarios (Table 3.). For linear motion, the mean absolute error was 0.34 m, with a standard deviation of 0.12 m. The maximum observed deviation was 0.63 m. For the circular ("P-shaped") path, the mean absolute error was 1.11 m, the standard deviation 0.29 m, and the maximum deviation 1.74 m.

These results confirm the stability of the Scarlett-type PDR during straight-line motion and highlight the expected increase in heading-related drift during curved trajectories.

Table 3. Extended statistical indicators.

Scenario	MAE (m)	RMSE (m)	Max Error (m)	Std Dev (m)
Linear	0.31	0.38	0.72	0.35
Circular (P)	1.05	1.28	1.98	1.22

BLE Segment Recognition (Qualitative Analysis)

A mechanism for recognizing the active spatial segment (aisle) was implemented based on RSSI value distribution. In most trials, the system accurately identified the current active zone, which is sufficient for practical retail scenarios (e.g., determining in which aisle the user is located).

When two tags were placed closer than approximately 2 m, signal overlap and RSSI variability occurred; in such cases, the closest tag was not always uniquely identified, although the correct zone was still recognized.

Localization precision can be further improved using adaptive RSSI filtering such as time averaging, sliding-window smoothing, or particle-based refinement.

Dwell Detection and Recalibration Threshold

A dwell status was triggered when the user remained within a 2 m radius of a reference tag for 30 seconds or longer. The experimentally estimated PDR error accumulation ranged from 0.068 to 0.077 m per meter walked.Based on these results, BLE recalibration was activated whenever cumulative drift exceeded approximately 2 m (typically after 25–30 steps of linear motion).

This adaptive mechanism achieves a balance between accuracy and energy efficiency — BLE corrections are applied only when necessary, while the PDR component maintains most of the trajectory tracking.

Summary of Experimental Evaluation

The combination of Scarlett-type PDR, BLE proximity corrections, and map constraints achieved meter-level accuracy without additional infrastructure or cloud-based computation: ≈ 0.4 m RMSE for linear and ≈ 1.3 m RMSE for complex trajectories.

The system reliably identified active segments or aisles and supported context-aware functionalities, such as user dwell analysis and targeted information display.

The proposed approach successfully met the design goal of achieving sub-2-meter localization accuracy in realistic retail environments.

COMPARATIVE EVALUATION WITH ALTERNATIVE INDOOR LOCALIZATION METHODS

To contextualize the performance of the proposed BLE–PDR system, Table 4. compares it with several representative localization methods commonly deployed in indoor environments. The comparison is based on published experimental results and the outcomes of this study.

The comparison demonstrates that the proposed hybrid system achieves a favorable balance between accuracy, cost, and infrastructural simplicity.

To contextualize the achieved results, the proposed system was compared with several widely used indoor localization approaches. Table 4 provides a concise overview of their typical accuracy, infrastructural requirements, and operational characteristics.

Table 4. Comparative overview of indoor localization methods for smart retail environments.

Method	Typical Accuracy	Infrastructure	Energy Use	Notes
BLE (proximity only)	2–5 m	ESL/Beacons	Very low	Accuracy strongly dependent on RSSI fluctuations
PDR-only	Drift accumulates (5–10% of path)	None	Low	Provides continuity but no absolute reference
Wi-Fi RTT	1–3 m	Wi-Fi APs	Moderate	Supports ToF but affected by multipath
UWB	0.1–0.5 m	Dedicated anchors	High	High accuracy; high cost
Proposed BLE–PDR	**0.4–1.3 m**	**Existing ESL tags**	**Low**	Requires no new infrastructure; fully on-device

SECURITY, ETHICAL CONSIDERATIONS AND LIMITATIONS

Privacy and On-Device Processing

The system was designed according to the privacy-by-design principle to ensure user data protection and avoid the intrusiveness of visual surveillance technologies. Unlike video analytics, all data are processed locally on the smartphone, with no personal information transmitted to external servers. The user's position is calculated entirely on the device, and the results are visible only to the user for navigation purposes.

Any transmission to a central server is possible only in anonymized and aggregated form, with the user's explicit consent. Such aggregate data may include average dwell time per zone or customer density but never contain individual identifiers.

During installation, users must be clearly informed about which data are collected (motion sensors, BLE scanning) and for what purpose. This model fully complies with GDPR requirements transparency, informed consent, and data minimization. Optionally, movement history can be stored on-device only, accessible solely to the user. In this case, retailers would receive only aggregated indicators, maintaining a balance between business analytics and data privacy.

Ethical Aspects and Risk of Secondary Surveillance

Although the system does not use video monitoring or direct personal identification, there remains a potential risk of secondary surveillance through behavioral pattern analysis. If user trajectories were correlated with personal identifiers (e.g., loyalty programs), behavioral habits and shopping patterns could be reconstructed.

Such scenarios raise ethical questions regarding the boundary between personalization and surveillance. Collected data should be used solely to enhance user experience such as optimizing product layouts, providing real-time personalized offers, or improving safety protocols but never for individual profiling.

Anonymization and data aggregation significantly reduce misuse risks, while the ability to disable tracking within the app gives users full control. Transparency, informed choice, and user autonomy are fundamental to building trust in BLE-based localization systems used in retail environments.

Signal Security and Resilience

Although BLE networks are simple and energy-efficient, they are vulnerable to spoofing attacks, where a malicious device imitates an existing tag's identifier. Such attacks can cause incorrect positioning or data manipulation. To increase resilience, the use of secure beacon formats such as Eddystone-EID (Ephemeral ID) is recommended. This format employs rotating, encrypted identifiers that change every few seconds or minutes. Only authorized clients possessing the proper key can decrypt and recognize these IDs, effectively preventing interception and replay attacks.

The experimental implementation in this study uses the standard iBeacon format with static UUID identifiers. However, for production environments, migration to Eddystone-EID or other rotating-identifier protocols is strongly advised.

Signal security can be further enhanced by restricting the BLE scanning domain — the application scans only within the store's physical boundaries and exclusively during active shopping sessions. This operational mode ensures transparent, secure performance in line with ethical intelligent-space design principles.

Adaptability to Diverse Users

The accuracy of the PDR algorithm depends strongly on the user's biomechanics. The baseline calibration is configured for an average healthy adult with a regular walking pace, whereas deviations (e.g., elderly users, individuals with reduced mobility, users with assistive devices, or children) can alter acceleration amplitude patterns, resulting in reduced accuracy.

To ensure universal applicability, two adaptive strategies are proposed:

1. Initial calibration – the application can prompt the user to walk a known distance (e.g., 5 m) to automatically adjust the Scarlett coefficients (α, β, γ) and step-detection thresholds.

2. Learning during operation – the system can adaptively refine parameters if it detects a persistent deviation between predicted and actual positions.

This adaptability enables precise tracking across a wide range of user profiles and forms the basis for an inclusive design in future system versions.

LIMITATIONS OF THE CURRENT WORK

Despite the encouraging experimental results, the proposed system has several limitations that must be considered when interpreting the findings and planning future research.

Limited Experimental Environment

Experiments were conducted in a controlled indoor area of approximately 30 m^2, which realistically simulates the conditions of a small retail store but does not reflect the complexity of larger commercial environments.

In such large-scale spaces, the number of BLE tags, users, and signal overlap significantly increase, potentially affecting scalability and the stability of RSSI values.

Future research should therefore include testing in real-world retail environments with higher levels of radio interference and spatial complexity.

Single-User Testing

All experiments were performed with a single user and one smartphone, without multi-user interactions. Simultaneous BLE scanning from multiple devices could lead to channel overlap and variations in RSSI distributions.

Consequently, additional experiments involving multiple users, varying orientations, and movement patterns are necessary to assess the system's robustness in realistic operational conditions.

Single-Floor Configuration

Testing was performed exclusively in a single-floor indoor environment. In multi-level buildings, BLE signals can leak between floors, making it difficult to distinguish vertical positioning.

In such cases, it is recommended to integrate a barometric sensor and implement multi-floor mapping with vertical zoning to ensure reliable floor-level separation and prevent misclassification of user locations.

Limited User Diversity

The experimental setup involved a single adult participant with a typical walking pattern. However, walking biomechanics significantly influence the amplitude and frequency of acceleration signals.

Future testing should include participants of different ages, genders, and walking speeds to evaluate the generalization capability of the PDR parameters and assess algorithm stability across diverse movement patterns.

Restricted Sensor Fusion

The current implementation relies solely on PDR and BLE as data sources. However, modern smart retail environments offer additional sensor modalities such as RFID tags, smart carts with motion sensors, shelf-embedded sensors, and Wi-Fi signals.

Integrating these modalities into a multi-sensor fusion framework could further improve accuracy, stability, and the semantic understanding of customer behavior, representing a promising direction for future development.

CONCLUSION

This study presents a hybrid localization system for smart retail environments that combines a BLE beacon network with smartphone inertial sensors to achieve accurate, energy-efficient, and privacy-preserving user localization without requiring any additional infrastructure.

The system employs a Scarlett-type PDR algorithm for relative motion tracking and a BLE proximity mechanism for periodic position correction. Unlike complex filter-based approaches (e.g., Kalman, Bayesian, or particle filters), the adopted methodology enables deterministic, real-time on-device processing, suitable for resource-limited mobile hardware.

Experimental evaluation demonstrated an average localization error of ≈0.4 m for linear motion and ≈1.3 m for curved trajectories, with an accumulated drift of 6–8 cm per meter walked. Based on these results, an adaptive recalibration threshold was introduced, triggering BLE correction when the accumulated PDR error exceeds ≈2 m, thereby preventing drift growth without increasing energy consumption.

The findings confirm that the BLE–PDR–map-constraint integration can deliver sufficient accuracy for practical indoor navigation without relying on cameras, external servers, or cloud processing.

Key system advantages include low implementation cost (BLE tags are inexpensive and long-lasting), scalability (incremental deployment by store zones), and a high level of data privacy ensured through local processing and adherence to the privacy-by-design principle.

Future work will focus on:

- Expanding testing to larger and multi-floor environments with multiple simultaneous users;
- Implementing dynamic PDR parameter adaptation based on individual walking characteristics;
- Integrating a particle filter for probabilistic BLE–PDR data fusion using map constraints;
- Transitioning to the Eddystone-EID beacon format with rotating encrypted identifiers to enhance signal security.

In summary, the proposed system provides a practical, scalable, and ethically aligned solution for indoor navigation and analytics in smart retail spaces, ensuring full user control over personal data.

The achieved results confirm that BLE–PDR fusion, combined with map-based constraints, can serve as a foundation for the next generation of on-device indoor localization systems in intelligent commercial environments.

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