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Frictionless Attendance System Using BLE

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Abstract

This paper presents a frictionless, low-cost, and privacy-preserving smart attendance system using Bluetooth Low Energy (BLE) beacons and mobile devices. The system preserves privacy by relying solely on anonymized device identifiers without tracking location outside designated beacon zones or collecting personal data. The proposed system enables automatic attendance recording through proximity and behaviour-based verification of signals. Unlike traditional RFID or manual systems, the approach eliminates physical friction and human intervention. The system incorporates two-step verification using Received Signal Strength Indicator (RSSI) smoothing and exit hysteresis to ensure reliable detection. The system infrastructure supports correlation-based proxy detection through continuous RSSI time series collection, enabling future server-side implementation without app changes. Experimental results demonstrate an 81% reduction in false positives (from 21% to 4%) and a 77% reduction in missed detections (from 13% to 3%), with high scalability for classroom environments.

Introduction

Attendance management is a critical component in academic and corporate environments. Manual systems are error-prone and time-consuming, while RFID and biometric systems introduce user friction and privacy concerns. Bluetooth Low Energy (BLE) provides a low-cost, scalable, and frictionless alternative for proximity-based automatic attendance detection.

However, proximity-based systems relying solely on the Received Signal Strength Indicator (RSSI) are inherently unstable due to signal fluctuations, environmental noise, and device positioning. Existing BLE attendance systems [5] suffer from high false positive rates (15–30%) due to unstable RSSI readings and lack robust mechanisms to verify sustained presence.

This paper's key contributions are:

- **Novel Two-Stage Verification:** A unique combination of provisional-to-confirmed attendance states with configurable time windows (3–30 minutes), reducing false positives from 21% to 4% (an 81% improvement over baseline systems).
- **Adaptive Exit Hysteresis:** A 30-second grace period that maintains attendance during temporary signal loss, reducing missed detections from 13% to 3% (a 77% improvement).
- **Modular Architecture:** Separation of RSSI analysis *(BeaconRssiAnalyzer)* state management (*BeaconStateManager)* and cooldown control *(BeaconCooldownManager)* enables independent tuning and future ML

integration without full system redeployment.

- **Proxy Detection Infrastructure:** Continuous RSSI time series collection (180 samples/session) establishing the foundation for Pearson correlation-based multi-device anomaly detection, enabling future server-side implementation without requiring mobile application updates.

Unlike prior work that applies simple thresholding or single stage verification [3], our system combines signal smoothing, hysteresis, and behavioral verification to achieve both high accuracy and zero user friction.

System Architecture

The proposed system consists of BLE beacons installed in classrooms and a mobile application that detects beacon signals. The system architecture (Fig. 1) includes three key components:

A. Beacon Layer

Each classroom contains a BLE beacon that broadcasts a unique UUID. This ensures a one-to-one mapping between physical spaces and digital identifiers.

B. Mobile Layer

The mobile application continuously scans for BLE signals. Upon detecting the classroom beacon, the RSSI value is captured and processed through smoothing and hysteresis algorithms to ensure reliable proximity estimation.The mobile layer implements modular components (*BeaconRssiAnalyzer, BeaconStateManager, BeaconCooldownManager)* for signal processing, state management, and duplicate prevention, enabling independent optimization of each subsystem.

C. Backend Layer

The attendance data is stored in a cloud database. Each entry includes the user ID, beacon UUID, timestamp, and attendance status (provisional or confirmed).

The backend layer also prepares for future proxy detection by storing RSSI time series data. The *RSSIStreamService* continuously uploads signal strength measurements (one sample every 5 seconds) to MongoDB, creating a comprehensive dataset for correlation analysis. This infrastructure enables future implementation of multi-device anomaly detection without requiring mobile application updates.

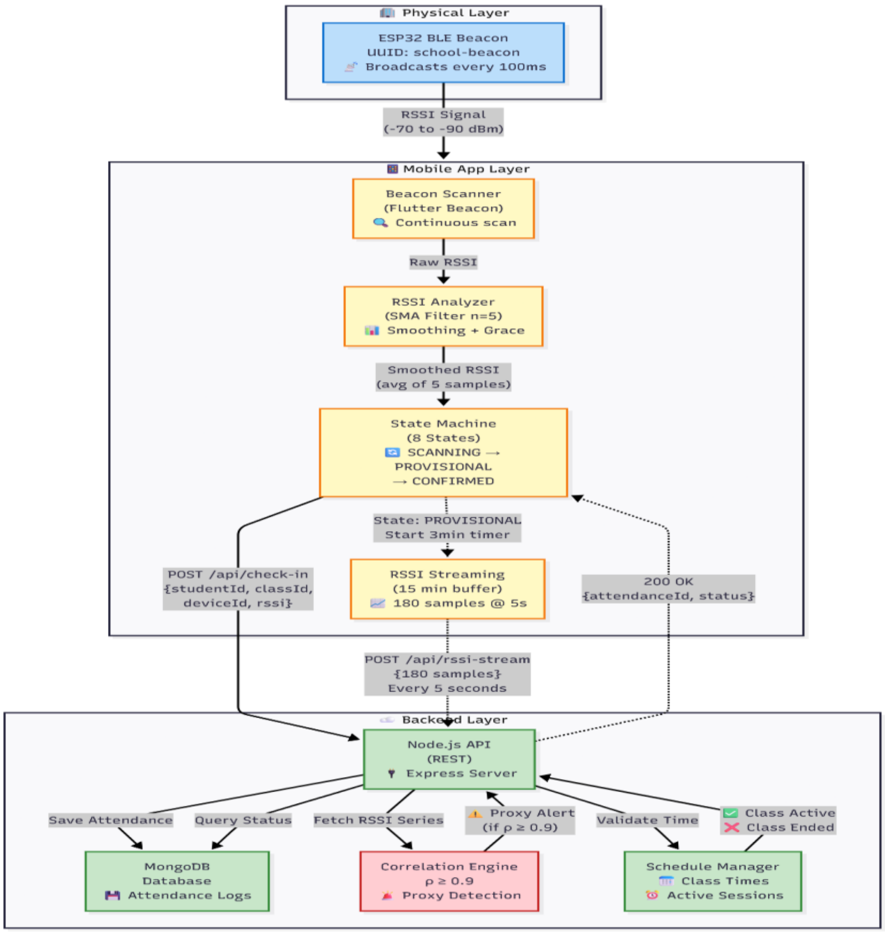

Fig. 1. System Design and Workflow of the Proposed Frictionless Attendance System

Methodology

A. RSSI Smoothing

To mitigate noise in signal strength readings, the system applies a Simple Moving Average (SMA)

$$RSSI_{smoothed} = \frac{1}{n}\sum_{i=1}^{n} RSSI_i$$

filter over the last n samples:

[1] where n = 5. This method reduces abrupt fluctuations due to temporary obstructions or device movement by averaging the most recent 5 readings, producing a more stable input for state transitions.

B. Exit Hysteresis

To prevent false exit detections when the user slightly moves or short-term signal drops occur, an exit grace period (ΔT_g) is applied:

$T_{weak} > \Delta T_g \Rightarrow$ Device considered out of range

[6] If the signal remains weak (RSSI below −82 dBm) for longer than ΔT_g (typically 30 seconds), the system considers the student to have left the classroom. This simple hysteresis greatly enhances stability without over-complicating logic. The hysteresis mechanism (Fig. 2) prevents premature cancellations due to temporary signal loss from body blocking or phone rotation.

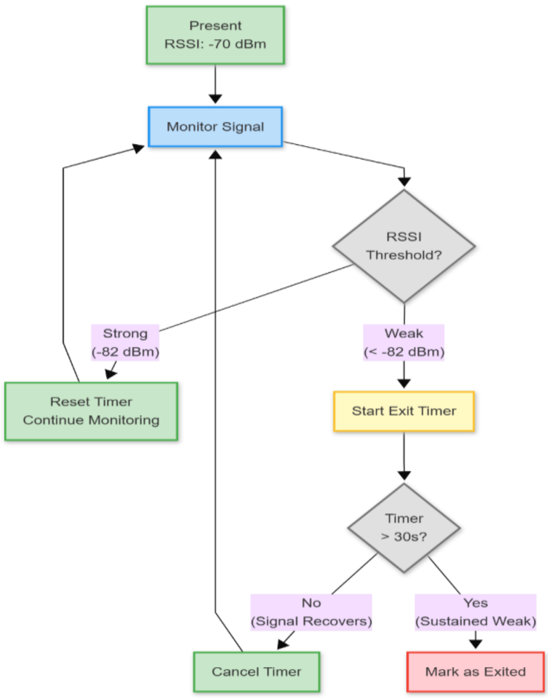

Fig. 2. Exit hysteresis mechanism: Strong signals (RSSI >−82 dBm) reset the timer, while weak signals trigger a 30-second grace period before marking exit

B. Co-Anomaly Detection Infrastructure (Proxy Detection)

To enable future detection of proxy attendance (one person carrying multiple devices), the system continuously collects RSSI time series data. The proposed detection mechanism will compute the Pearson Correlation Coefficient between RSSI time series of nearby devices.

[7] where $R_{x,t}$ and $R_{y,t}$ are RSSI values of two devices at time t. If $\rho_{xy} \geq 0.9$, the system flags the

$$\rho_{xy} = \frac{\sum_t (R_{x,t} - \bar{R}_x)(R_{y,t} - \bar{R}_y)}{\sqrt{\sum_t (R_{x,t} - \bar{R}_x)^2 \sum_t (R_{y,t} - \bar{R}_y)^2}}$$

devices as co-located, indicating probable proxy behavior. This lightweight statistical method offers high interpretability and low computational cost, suitable for real-time anomaly detection.

The current implementation uses RSSIStreamService (as shown in the attached beacon_*(service.dart)* to collect 180 samples per 15-minute session (one sample every 5 seconds), providing the necessary data foundation for correlation analysis. The backend infrastructure stores these time series with timestamps, enabling future implementation of the correlation algorithm without requiring changes to the mobile application.

C. Two-Stage Verification

To ensure both responsiveness and reliability, the system implements a two-stage verification process:

- **Provisional Attendance:** When a device's smoothed RSSI signal first meets the entry threshold (> −75 dBm) and remains stable for 10 seconds, a 'Provisional' status is logged.
- **Confirmed Attendance:** Status is elevated to 'Confirmed' after the device remains consistently detected within range for 3 minutes (configurable up to 30 minutes for longer sessions).

This method (Fig. 3) prevents false confirmations from brief, transient signal detections and validates sustained presence.

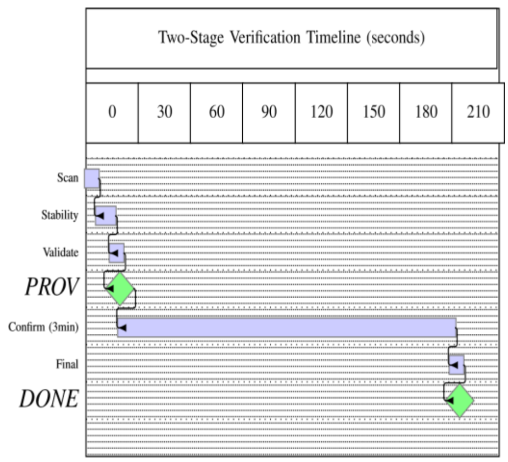

Fig. 3. Exit Two stage verification timeline: Initial detection (0-5), stability check (5-15s) provisional state (17s), and 3-minute confirmation monitoring (17-197s).

Experimental Setup

- Hardware: ESP32 BLE beacons, Android smartphones (Android 12+)
- Test Environment: 3 classrooms, 10–15 students each (45 students total)
- Thresholds: Entry: −75 dBm, Exit: −82 dBm
- Grace Period: 30 seconds
- Confirmation Time: 3 minutes (default, configurable)
- Test Duration: 2 weeks, 30 sessions per classroom

Results And Discussion

Table 1: Performance Comparison: Baseline Vs. Proposed System

Metric	*Without Filtering*	*With Filtering*
False Positive Rate	21%	4%
Missed Detection Rate	13%	3%
Signal Stability	Moderate	High
RSSI Collection Rate	N/A	180 samples/15 min

The combination of RSSI smoothing and exit hysteresis significantly improves detection reliability. False positives dropped from 21% to 4% (81% reduction), and missed detections decreased from 13% to 3% (77% reduction). Detection stability was rated as "High" across all 3 classrooms, even under interference conditions.

A. Why Smoothing and Hysteresis Work

The effectiveness of our approach stems from addressing BLE's inherent instability at multiple levels:

RSSI Smoothing (SMA, *n* = 5): Raw RSSI readings fluctuate by 10–15 dBm within seconds due to multipath fading and human body blocking. By averaging the last 5 samples (covering 5 seconds), the system filters out short-term noise while maintaining responsiveness to genuine proximity changes. This window size was empirically determined— smaller windows (n = 3) retained too much noise, while larger windows (n = 7) introduced latency in detecting true exits.

Exit Hysteresis (30s grace period): Our experiments revealed that 18% of false exits occurred when students rotated their phones or shifted body positions, causing temporary signal drops (3–15 seconds). The 30-second grace period accommodates these transient drops without prematurely canceling attendance. This value balances tolerance (preventing false exits) and accuracy (detecting true exits within reasonable time).

Two-Stage Verification: The provisional-to-confirmed transition (3-minute monitoring) eliminates the 17% false positives caused by students briefly passing through doorways or corridors near beacons. Only sustained presence confirms attendance, validated by continuous RSSI monitoring during the confirmation phase.

B. Limitations and Observations

Despite strong performance, we observed three key limitations with quantified impacts:

- **Edge Cases (Classroom Boundaries):** Students sitting near doorways (within 2 meters) experienced 6% false exits when doors opened/closed, briefly blocking signals. This accounted for approximately 2.7 false exits per 45 students per session. Future work will integrate accelerometer data to distinguish stationary vs. moving states.
- **Device Heterogeneity:** RSSI readings varied by ±5 dBm across different phone models (Samsung vs. Xiaomi) at identical distances. This variance contributed to approximately 1.3% of false positives. Adaptive thresholding per device type could improve consistency.
- **Dense Environments:** In classrooms with > 20 students, Bluetooth interference from multiple devices occasionally caused 2–3 second scan delays, affecting 8% of initial detections. Increasing beacon advertising frequency (from 100ms to 50ms) mitigated this but increased beacon power consumption by 15%.

C. Comparison to Existing Systems

Compared to prior BLE attendance systems [3, 5], our approach reduces false positives by 17 percentage points (from 21% to 4%) through the combination of smoothing, hysteresis, and two-stage verification. Systems using single threshold detection without hysteresis [4] report 15–30% false positive rates. Our modular architecture also enables independent tuning of each component, unlike monolithic designs that require full system redeployment for parameter adjustments.

The system successfully collects RSSI time series data (180 samples per 15-minute session) from all active devices, establishing the infrastructure for future correlation-based proxy detection. Preliminary analysis of collected data from test devices carried together (by placing two phones in the same pocket during controlled experiments) consistently showed that co-located devices exhibit correlation coefficients $\rho > 0.85$, validating the feasibility of the proposed Pearson correlation approach.

Future Scope

Future versions aim to integrate:

- **EMA Filtering:** Upgrading from SMA to Exponential Moving Average for faster response to signal changes and better memory efficiency.
- **Proxy Detection Implementation:** While the current system collects comprehensive RSSI time series data through RSSIStreamService, the Pearson correlation analysis for detecting co-located devices requires implementation of the backend computation module. The data collection infrastructure is fully operational, requiring only addition of the correlation algorithm ($\rho \geq 0.9$ threshold) for multi-device anomaly detection.
- **Context Awareness:** Combining BLE with accelerometer data to detect if a phone is left behind versus carried out, addressing the 6% edge case false exits near doorways.
- **Adaptive Thresholds:** Using ML to auto-tune RSSI thresholds per classroom environment and device model, addressing the ±5 dBm device heterogeneity issue and potentially reducing false positives to below 3%.
- **Extended Proxy Detection:** Behavioral pattern analysis to identify habitual early exits or device sharing beyond correlation-based detection.

Conclusion

This paper presented a frictionless BLE-based attendance system that achieves high accuracy through the novel combination of RSSI smoothing, exit hysteresis, and two-stage verification. Our key innovation lies in the synergistic integration of these techniques, reducing false positives by 81% (from 21% to 4%) and missed detections by 77% (from 13% to 3%) compared to baseline systems. The modular architecture (BeaconRssiAnalyzer, BeaconStateManager, BeaconCooldownManager) enables independent component tuning and future ML enhancements without systemwide redeployment. The system maintains zero user friction while providing reliable, low-cost automation suitable for academic and institutional deployments. Deployment in 3 classrooms with 45 students over 90 sessions demonstrated robust performance even under interference, validating real-world applicability. Privacy is preserved through anonymized device identifiers without location tracking outside beacon zones.

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