RSSI-Based Passenger Movement Classification for Non-Intrusive Public Transport Monitoring

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***Abstract*—Accurate monitoring of passenger flows in public transport is essential for service optimization and network planning, yet traditional counting methods face limitations in coverage, cost, and privacy preservation. This paper presents a novel approach for classifying passenger movements using temporal sequences of WiFi Received Signal Strength Indicator (RSSI) measurements. We introduce a dataset collected in a controlled experimental environment that simulates public transport scenarios, capturing the distinctive signal patterns associated with four fundamental movement classes: boarding the vehicle, alighting from the vehicle, remaining inside, and remaining at the bus stop. By analyzing the temporal evolution of RSSI values over ten-second observation windows, our approach enables non-intrusive distinction between static and transitional states without requiring specialized hardware or compromising passenger anonymity. Experimental evaluation using multiple machine learning classifiers demonstrates the feasibility of RSSI-based movement classification, providing a cost-effective complement to existing automatic passenger counting systems for intelligent transportation applications.**

***Index Terms*—Passenger counting, RSSI fingerprinting, WiFi sensing, public transport, machine learning, intelligent transportation systems, urban mobility**

I. Introduction

Urban mobility represents one of the most pressing challenges facing modern cities, as more than 75% of European Union citizens currently reside in urban areas [1]. Inefficient transportation systems contribute approximately 24% of greenhouse gas emissions, underscoring the urgent need for intelligent and sustainable mobility solutions [2]. Public transport networks play a pivotal role in addressing these challenges; however, their effective management requires accurate and continuous data regarding passenger flows across the network. Real-time passenger occupancy information supports dynamic scheduling and resource allocation, enabling transport operators to enhance service quality while contributing to sustainable urban development [3].

Traditional approaches to passenger counting and origin-destination (OD) matrix estimation rely on manual surveys, ticketing systems, or dedicated hardware such as infrared sensors and automated passenger counting (APC) devices [4]. While these methods have proven useful, they present significant limitations including high deployment costs, incomplete spatial coverage, privacy concerns associated with video-based systems, and the inability to provide continuous, non-intrusive monitoring of passenger movements [5]. Furthermore, conventional ticketing systems often fail to capture the complete passenger journey, as exit validation is frequently absent in many public transport networks [6]. Recent comprehensive reviews of passenger counting technologies have identified wireless sensing as a particularly promising direction, combining cost-effectiveness with privacy preservation [7].

The proliferation of personal wireless devices, particularly smartphones, has opened new avenues for non-intrusive passenger detection and tracking. WiFi-enabled devices continuously emit probe requests and maintain connections with nearby access points, generating Received Signal Strength Indicator (RSSI) signatures that can be leveraged for localization and movement pattern recognition [8]. Unlike camera-based systems, WiFi sensing approaches inherently preserve passenger anonymity while providing valuable insights into mobility patterns [9]. This characteristic is particularly relevant in the context of increasing privacy regulations, as wireless signal analysis enables presence monitoring without collecting personally identifiable visual data.

Recent advances in Channel State Information (CSI) extraction have further enhanced the capabilities of WiFi-based passenger counting systems, achieving remarkable accuracy rates exceeding 94% in controlled environments through cooperative sensing with multiple receivers [10]. However, CSI-based approaches require specialized hardware for channel estimation and are computationally intensive, limiting their practical deployment in resource-constrained settings. In contrast, RSSI-based methods offer a more accessible alternative, requiring only standard networking equipment while still providing meaningful signal fingerprints for classification tasks [11]. The inherent trade-off between sensing granularity and deployment practicality motivates the exploration of RSSI-based solutions for large-scale transit applications.

This paper presents a novel approach to passenger boarding and alighting classification using temporal sequences of RSSI measurements. The proposed methodology enables the distinction between four fundamental movement patterns: remaining inside the vehicle, remaining at the bus stop, boarding the vehicle, and alighting from the vehicle. By analyzing the temporal evolution of signal strength over a ten-second observation window comprising ten sequential measurements, our approach captures the distinctive signatures associated with each movement pattern without requiring precise localization or continuous tracking of individual devices.

The main contributions of this work are threefold. First, we introduce a publicly available dataset specifically designed for RSSI-based passenger movement classification, collected in a controlled experimental environment that simulates real-world public transport scenarios with both isolated and noisy conditions. Second, we present a comprehensive analysis of temporal RSSI patterns across different movement classes, demonstrating the feasibility of distinguishing between static and transitional states using standard WiFi access point equipment. Third, we evaluate multiple machine learning classifiers for this task, providing insights into the most effective approaches for real-time passenger flow estimation in practical deployments.

The remainder of this paper is organized as follows. Section II reviews related work in passenger counting, WiFi-based sensing, and RSSI fingerprinting. Section III describes the experimental setup and data collection methodology. Section IV presents the classification results, followed by a discussion in Section V. Finally, Section VII concludes the paper and outlines directions for future work.

II. Related Work

The challenge of accurately monitoring passenger flows in public transport has attracted considerable research attention, resulting in diverse technological approaches ranging from dedicated sensing hardware to opportunistic wireless signal analysis. This section reviews the most relevant contributions across three interconnected domains.

A. Automatic Passenger Counting Systems

Traditional Automatic Passenger Counting (APC) systems primarily rely on infrared sensors, pressure mats, or video-based detection installed at vehicle entrances [4]. Pronello and Garzón Ruiz [5] evaluated commercial video-based APC systems under real-world conditions, revealing that claimed accuracy rates of 98% often deteriorate to 53–74% in practice. Computer vision approaches have advanced with deep learning, with Wiboonsiriruk et al. [12] achieving 94% accuracy using object detection and tracking. However, vision-based systems remain constrained by occlusion, lighting variations, and privacy concerns regarding visual data collection.

B. WiFi-Based Sensing for Passenger Detection

The ubiquity of WiFi-enabled devices has motivated research into wireless signal analysis for mobility monitoring. Myrvoll et al. [13] pioneered WiFi signatures for public transport passenger counting through probe request analysis. Nitti et al. [8] developed iABACUS, achieving 100% detection accuracy in static scenarios and approximately 94% in dynamic conditions.

Channel State Information (CSI) offers richer information than RSSI alone. Guo et al. [10] proposed an RSSI-assisted CSI-based counting system achieving accuracy exceeding 94% through adaptive feature fusion. However, CSI requires specialized hardware and is computationally demanding, whereas RSSI is readily available from standard equipment. Fabre et al. [14] compared machine learning algorithms for WiFi-based ridership estimation, finding Light Gradient Boosting Machine provided accurate boarding and alighting predictions. Simončič et al. [9] developed a non-intrusive WiFi detection system achieving over 96% accuracy despite MAC address randomization.

C. RSSI Fingerprinting and Movement Classification

RSSI fingerprinting has been extensively studied for indoor localization [11]. Recent work extends RSSI analysis to trajectory and movement classification. Wang et al. [15] proposed treating continuously measured RSSI values as temporal sequences, aligning with our methodology of leveraging signal strength evolution over time. Servizi et al. [16] addressed bus boarding and alighting detection using smartphone-based Bluetooth sensing, highlighting the complexity of distinguishing transitional states. Cerqueira et al. [6] demonstrated the importance of understanding complete passenger journey patterns for origin-destination matrix inference.

D. Research Gap and Contribution

While significant progress has been made in both passenger counting and wireless signal-based sensing, the specific application of machine learning to classify passenger movement patterns from RSSI time series remains underexplored. Existing WiFi-based approaches have primarily focused on aggregate counting or statistical inference, rather than developing classifiers that can distinguish fine-grained movement patterns such as boarding versus alighting.

Our work addresses this gap by framing passenger movement detection as a supervised classification problem, where the temporal evolution of RSSI values over a short observation window serves as the input feature vector. This approach enables real-time classification of individual device trajectories, which can subsequently be aggregated to estimate passenger flows and contribute to origin-destination matrix construction.

Furthermore, unlike studies that rely on multiple access points or complex sensor fusion, our approach uses a single WiFi access point positioned at the vehicle door, minimizing infrastructure requirements while still achieving discriminative power through the temporal dynamics of signal strength.

III. Experimental Setup

IV. Results

V. Discussion

VI. Contributions

VII. Conclusions

A. Future Work

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