DeMo: Experiences of Deploying a Large-Scale Indoor Delivery Monitoring System

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***Abstract*—The delivery of goods to numerous indoor stores poses significant safety risks, with heavy, high-stacked packages on delivery trolleys posing a potential hazard to passersby. This paper reports our experiences of developing and operating DeMo, a practical system for real-time monitoring of indoor delivery. DeMo employs sensors attached to trolleys, utilizing Inertial Measurement Unit (IMU) and Bluetooth Low Energy (BLE) readings to detect delivery violations, such as speeding and the use of non-designated delivery paths, and ensure accurate matching of each delivery to its intended destination store. Unlike typical indoor localization applications, DeMo addresses unique challenges, including sensor placement and the complex electromagnetic characteristics encountered in underground settings. Specifically, DeMo adapts the classical logarithmic radio signal model to facilitate fingerprint-free localization, significantly reducing deployment and maintenance costs. DeMo has been operating since May 2020, covering more than 200 shops with 74,537 deliveries (6193.2 km) across 12 subway stations in Hong Kong. DeMo's 4-year operation witnessed a significant violation rate drop, from 19% (May 2020) to 0.9% (Mar 2024).**

***Index Terms*—Sensor network, mobile computing, Bluetooth low energy.**

I. Introduction

Indoor localization has been extensively studied by the academic community [4], [5], [47], [52], [55], [75], [77]. Recently, commercial large-scale indoor localization systems have emerged, leveraging two decades of research to benefit end customers—for example, mall navigation [38], [55] and presence detection [21], [22], and even providing opportunities for monetization [58].

Fig. 1. Indoor delivery in an MTR station.

In this paper, we explore a unique and significant application within the domain of indoor localization: *indoor delivery monitoring*. Many public spaces, including airports, subway stations, and malls, often contain dense retail areas and experience high visitor traffic. The delivery of goods to these stores (Fig. 1) presents considerable safety concerns, as the potential fall of heavy, high-stacked packages from delivery trolleys can injure passersby. These specific indoor environments may exacerbate such risks: typically, there are no corridors designated solely for delivery purposes; uneven surfaces, including slopes, tactile paving, and contraction joints, contribute to the instability of packages; furthermore, delivery personnel may use utilize passenger lifts, the acceleration and deceleration of which may cause packages to topple. Careless practices in indoor delivery have led to severe injuries or even deaths [1], [17], [27], [28], [57]. For example, in a recent accident, multiple packages fell and paralyzed a nearby passenger when a delivery worker was using a passenger lift to transport a trolley full of goods [57]. In crowded indoor environments, delivery accidents can be more severe than their outdoor counterparts [6], [46], potentially triggering cascading accidents such as crowd collapses and stampedes, with death tolls reaching into the hundreds.

As an advocate for indoor delivery safety, the Hong Kong Electrical and Mechanical Services Department (HK EMSD) has strictly monitored delivery violations in Hong Kong's Mass Transit Railway (MTR) stations. MTR boasts a daily ridership

Received 14 August 2024; revised 27 June 2025; accepted 3 July 2025. Date of publication 29 July 2025; date of current version 5 November 2025. This work was supported in part by NSF China under Grant 62102332, Grant CityU 21216822, Grant CityU APRC 9610491, and Grant CityU 11206023, in part by Research Grants Council Collaborative Research Fund under Grant C1045-23G, and in part by the RGC General Research Fund of Hong Kong under Grant 16201625. Recommended for acceptance by L. Wang. *(Corresponding author: Zhimeng Yin.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Human Subjects Ethics Sub-Committee of City University of Hong Kong under Application No. HU-STA-00000208.

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Digital Object Identifier 10.1109/TMC.2025.3588900

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TABLE I
LARGE-SCALE INDOOR OPERATIONAL SYSTEMS

System	Technique	Signal	Application
MLoc [38]	Fingerprinting	B+G, IMU	Navigation
Tencent [55]	Fingerprinting	WiFi, IMU	Navigation
myCoex [32]	Fingerprinting	WiFi	Navigation
aBeacon [21]	Proximity det.	BLE	Presence det.
VALID [22]	Proximity det.	BLE	Presence det.
DeMo	Prop. model	BLE, IMU	Delivery mon.

"B+G" represents BLE and geomagnetic fields; "det." means detection; "prop." is for propagation; "mon." represents monitoring.

exceeding 5 million (Feb 2023). Henceforth, its stations are dense with passengers, stores, and indoor deliveries. EMSD has established four categories of delivery violations in MTR stations: (1) speeding (trolley moving speed $\geq$ 1.5 m/s), (2) using non-designated delivery paths, (3) using passenger lifts without prior permission, and (4) conducting delivery in peak hours. To ensure compliance with these regulations, since 2010, MTR has employed safety staff to manually monitor delivery behaviors. This process requires staff to physically follow the delivery workers and manually record any observed violations. Clearly, this approach is inaccurate, particularly in estimating speeds, not scalable, and labor-intensive.

To address the drawbacks of manual monitoring, we collaborated with HK EMSD and MTR to develop a fully automated indoor delivery monitoring system, referred to as DeMo. In this paper, we report our four-year experiences of developing, deploying, and maintaining DeMo. Our system was commercially deployed in 12 MTR stations for monitoring 70K+ deliveries to 200+ stores since May 2020.

At first glance, it might seem feasible to straightforwardly apply an existing indoor localization solution (Table I) as is: by tracking the delivery worker's location, ideally one can find out the speed and path of the delivery in real time. However, we encounter several unique challenges and practical constraints that render off-the-shelf indoor localization solutions inapplicable. First, *sensor placement differs significantly*. Unlike previous solutions that assume users carry hand-held smartphones for localization, for indoor delivery, workers usually attach sensors to the trolley. Therefore, motion sensor readings do not exhibit periodical footstep-incurred patterns that are widely leveraged for online location tracking [42], [65]. Again due to the sensor placement, sensor readings are significantly disturbed when the trolley moves over special ground surfaces (e.g., tactile pavings). Second, compared to prior localization systems' target environments (e.g., shopping malls), HK's MTR stations are usually *underground and bear much more complex electromagnetic characteristics* due to operating trains. As a result, we are unable to utilize commonly employed features, such as geomagnetic field (GMF) strength. Due to the same reason, we are not even able to obtain the accurate moving direction that is crucial for position tracking. Third, due to *privacy concern and loud noises* in MTR stations, vision-based or acoustic-based localization methods are not feasible; given the *constraints of device form factor and energy usage*, we are not allowed to adopt WiFi-based localization either, which was heavily researched [15], [62], [76] and commercially deployed [32], [55]. Fourth, HK EMSD and MTR also hope to *minimize the preparation and maintenance overhead*. We thus decide to not use a fingerprint-based approach that was adopted by almost all prior commercial indoor navigation solutions [32], [38], because training and maintaining the fingerprint database requires significant labor in crowded MTR stations. Lastly, the compact layout and narrow storefronts of shops within MTR stations make it difficult to determine delivery destination shops solely based on positioning results accurately. To address the aforementioned challenges, DeMo exclusively utilizes cost-effective, lightweight Bluetooth Low Energy (BLE) beacons as infrastructure. To further lower the deployment bar, instead of relying on BLE beacons' RSSI readings as location fingerprints, we employ a simple RSSI-distance model as the core localization mechanism. This model is universally applicable across all MTR stations, eliminating the need for site-specific training and frequent updates to the fingerprint database. While RSSI propagation modeling has been extensively explored [5], [7], [15], [39], [54], our contribution lies in *adapting the classical logarithmic model [54] to complex indoor environments, and for the first time, demonstrating its effectiveness in enabling fingerprint-free localization in large-scale commercial deployment*. Specifically, in MTR stations where occlusion, interference, and dynamic crowds are prevalent, abrupt RSSI fluctuations and weak signal strengths can introduce significant ranging errors. To address this, we modify the classical free-space propagation model to better handle these challenges. Additionally, we calibrate our model through one-time training and deploy it uniformly across all MTR stations. Experimental results show that our adjusted model significantly outperforms existing methods [5], [7], [15], [39], [54], many of which require complex tuning techniques like ray tracing. To enhance store identification accuracy, DeMo adopts a transformer-based algorithm specifically designed for this task. To reduce computational overhead, we simplify the model by removing the decoder module and employing an encoder-only architecture that efficiently analyzes BLE RSSI data collected by sensors on delivery trolleys.

On the trolley side, we engineer a lightweight sensor with an inertial measurement unit (IMU) and a BLE RSSI receiver. Our sensing algorithm can work with diverse sensor placement: hand-holding, in-pocket, and most importantly, sensor attaching to the trolley. For trolley-attached placement, we develop robust algorithms that identify three types of road surfaces appearing in MTR stations: normal road, tactile paving, and contraction joints (Fig. 8). The detected surface type is then utilized to improve the speed estimation. To overcome the aforementioned challenge of missing moving direction, we design a customized particle filter (PF) that leverages the RSSI-distance model and estimated speed to accurately localize the trolley, without requiring explicit direction reading. To address the practical constraints posed by stores' narrow storefronts, we leverage the transformer model by employing an encoder-only architecture that is efficient and tailored to the sensor's capabilities. Impressively, our customized deep learning model not only functions effectively but also achieves a remarkable store detection accuracy of 97.8%. Last but not least, we integrate the above components

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(RSSI model, speed measurement, surface detection, PF-based localization, store detection), together with other essential modules (floor plan processing, violation detection/alarming, delivery recording, etc.), into the holistic system of DeMo. The overall development/testing took 6 months. We then worked with HK EMSD and MTR to commercially deploy DeMo in 12 MTR stations in May 2020. We conduct thorough evaluations using two complementary sources: (1) data collected from our 4-year deployment (74K+ deliveries to 200+ shops, with 6193.2 km total travel distance), and (2) 15-day controlled experiments (900 deliveries with 54 km travel distance, with ground truth). Our key results are as follows.

• DeMo's 4-year operation witnessed a significant violation rate drop, from 19% (May 2020) to 0.9% (Mar 2024). This demonstrates DeMo's influence on delivery behaviors.

• We conducted an A/B test to confirm that the improvement of delivery behaviors is indeed due to DeMo's violation detection/warning capability instead of delivery workers' perception of our sensing devices.

• In contrast to the common belief that a propagation model suffers from large errors, our integrated design yields a mean positioning error of 2.17 m in MTR stations without the need for labor-intensive site surveys.

• DeMo achieves accurate road surface detection, which further facilitates trolley speed estimation (mean error 0.31 m/s). Both only use IMU sensors.

• In the constrained storefronts of MTR stations, the encoder-only transformer model demonstrates superior performance over other methods (Fig. 16), achieving an impressive accuracy of 97.8%, while maintaining robust operation on computationally limited sensors (e.g., Raspberry Pi).

• Compared to manual delivery monitoring used before 2020, DeMo improved the monitoring coverage (i.e., the fraction of detected delivery events) from 53% to 91%, and meanwhile reduced the operational cost by 10X.

• DeMo achieves perfect detection for all violation types with speeding being the only exception. For speeding violations, DeMo reported 9.3% FP and 2.4% FN ;[1] the real-time warning is even less accurate. Therefore, DeMo is not intended for law enforcement actions, similar to prior systems (e.g., detecting reckless driving [81]). Despite this limitation, DeMo was endorsed by MTR safety staff: we invited 20 staff to participate in a questionnaire survey; 95% of the participants agree or strongly agree that DeMo can improve delivery safety.

To summarize, our contributions are as follows:

• We proposed and implemented DeMo, the first commercially deployed indoor delivery monitoring system for the complex and constrained environments of subway stations, offering a cost-effective and scalable solution for reliable operation.

• We share the insights and operational experiences gained from DeMo's four-year deployment, addressing challenges such as uncertain sensor placement and complex electromagnetic interference to guide the development and optimization of future indoor monitoring systems.

• DeMo has significantly enhanced the safety of MTR stations, benefiting millions of riders every day.

• DeMo exhibits robust performance and significant potential for broader indoor applications, including property management, where it can monitor shuttle vehicles in malls and track luggage carts in airports.

Ethical Consideration: Our IRB-approved study complies with the agreement between us and HK MTR. We did not collect any personally identifiable information (PII) of delivery workers or passengers. Neither was MTR willing to release data for the actual incidents because of privacy concerns.

Data Release: To support future research and provide practical insights into the operation of DeMo, we have released our collected IMU and BLE datasets, source code, and a demonstration video on GitHub [18].

TABLE II
AN EXAMPLE OF MANUAL DELIVERY REPORT

Field	Value
Station Code	KXX
Entry/Exit	A
Start time	5/10/23 10:05
Shop ID	K001
Violation type	2

II. BACKGROUND AND MOTIVATION

Delivery Violations: The MTR is a major public transportation network that transports around 5 million daily passengers in HK. In order to cater to the daily needs of commuters, MTR stations offer a variety of shops, such as food and beverage, health and beauty, banking, and convenience stores, similar to typical small malls in many countries. Due to the crowded MTR stations, indoor delivery poses a potential risk and HK EMSD requires strict monitoring of delivery behaviors in MTR stations. In addressing the particular context of delivery within MTR stations, the EMSD defines the violations as follows.

• *Violation 1:* speeding (trolley moving speed $\geq$ 1.5 m/s for more than 3 seconds).

• *Violation 2:* non-designated delivery path (entry/exit/path).

• *Violation 3:* usage of passenger lift without prior permission from the station.

• *Violation 4:* deliver during peak hours (07:00-10:00 am and 4:00-8:00 pm).

Manual Monitoring and Limitations: To ensure the safe execution of deliveries following government guidelines, MTR stations employ additional safety staff for manual monitoring. These safety staff need to accompany each delivery, warn delivery workers once they observe a violation, and file delivery reports for future action. These delivery reports include the time of delivery, path, and violation type (if there exists a violation). Table II shows one example of a delivery report.

Not surprisingly, the existing manual system exhibits significant limitations. (1) It is difficult to visually monitor delivery

[1] FP is less of a concern since MTR stations hope to slow down delivery speeds for passenger safety.

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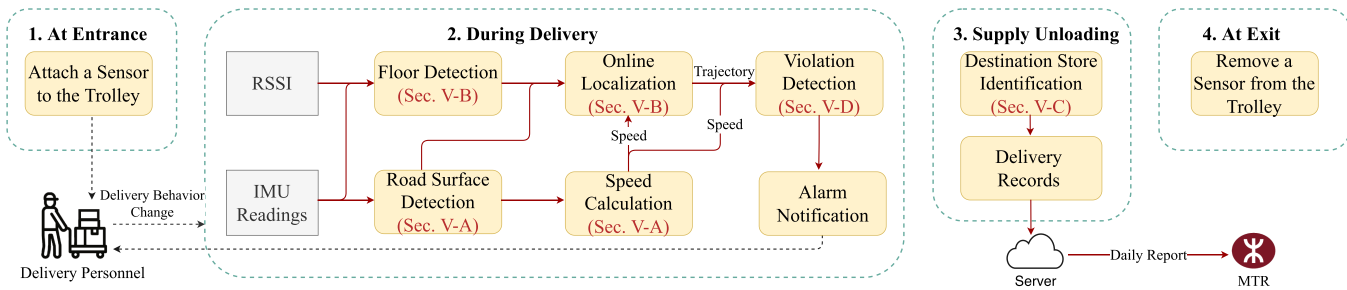

Fig. 2. DeMo system overview (online operational phase).

workers' moving speed. (2) Manual recording requires considerable human resources, with a safety staff member required for each delivery. It is impossible for one safety staff to monitor multiple deliveries concurrently, resulting in monitoring failures. (3) The labor cost is significant. Each station requires multiple safety staff depending on its scale, directly contributing to high expenses. These limitations have prompted the design of a fully automated system, which promises reliable monitoring services at reduced costs.

III. System Overview

A. Design Goal

DeMo aims to monitor indoor deliveries, identify potential violations, and ensure an accurate match of each delivery to its destination store. Then, each delivery's record will be submitted to MTR for further management. As required by MTR, DeMo needs to fulfill the following critical requirements:

• *Reliable violation detection:* This ensures comprehensive oversight of deliveries, allowing for the detection of non-compliance issues and accurate matching of each violation to its corresponding destination store.

• *Low-cost for large-scale operation:* DeMo is designed to be economically viable, facilitating scalability and the management of a vast number of indoor deliveries without incurring prohibitive costs.

• *Privacy protection:* Considering privacy concerns, our solution eschews vision-based methods and explores alternative approaches that protect passenger privacy.

B. Challenges

Designing DeMo requires us to address several unique challenges and practical constraints as follows.

Uncertain Sensor Placement: In prior solutions, users typically use handheld smartphones for positioning. However, in this indoor delivery scenario, delivery workers commonly mount sensors on trolleys, accounting for 95% of deliveries. Consequently, the motion sensor readings lack the periodic footstep patterns that are typically used for location tracking. Furthermore, we observe that the trolley movement significantly disturbs sensor readings, when they move over certain road surfaces, resulting in considerable errors in speed detection.

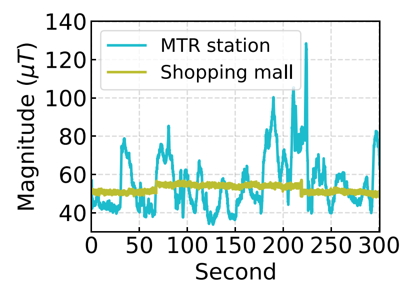

Fig. 3. Variations in GMF strength over time at a shopping mall and MTR station.

TABLE III
Storefront Distribution

Width	3 - 4 m	4 - 5 m	5 - 6 m	6 - 7 m	>7 m
Ratio (%)	31	11	12	27	19

Therefore, the uncertain sensor placement presents a significant challenge in the design of the system.

Complex Electromagnetic Characteristics: Different from conventional indoor settings, MTR stations exhibit complex electromagnetic characteristics, making it difficult to estimate the direction. To validate this, we collected GMF strength at various locations within subway stations, encompassing entry, exits, and open areas. Results indicate that magnetic fields within subway stations are highly unstable, as illustrated in Fig. 3. Over time, GMF readings at a fixed location exhibited erratic and unpredictable fluctuations. In contrast, similar experimental setups in other indoor environments, such as shopping malls, yielded much more stable magnetic field readings with small fluctuations. Consequently, due to the unpredictable and irregular changes in magnetic field readings caused by the continuously operating trains, GMF cannot be reliably used to ascertain the accurate moving direction for precise positioning tracking.

Constrained Storefront Dimensions: Within the confines of MTR stations, the physical layout of stores poses a unique challenge for inferring delivery destination stores. Intuitively, the destination store could be directly inferred from the positioning results. However, in MTR stations, most storefronts are relatively narrow, as shown in Table III, with stores having a frontage of 3-4 meters accounting for 31% of the total. The narrowness of these storefronts means that positioning results

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alone are insufficient to accurately determine the intended delivery destination. Thus, this practical constraint represents another significant challenge in system design.

C. System Overview

DeMo operates in two phases: *offline preparatory phase* and *online operational phase*.

Offline Preparatory Phase: In this phase, we design customized sensors to be attached to trolleys for delivery monitoring. BLE beacons are then strategically deployed within MTR stations, balancing monitoring reliability with deployment and maintenance costs. To eliminate the high costs of radio fingerprinting commonly associated with wireless localization systems, we employ a Received Signal Strength Indication (RSSI) to distance model, which provides reliable accuracy and is easily adaptable across various scenarios. For destination store identification, we train a BLE-Former model based on transformer architecture, utilizing target store labels collected from several hired delivery personnel. Additionally, we process the floor maps to record detailed information, such as road surface types and delivery areas. The specifics of the preparatory phase are further discussed in Section IV.

Online Operational Phase: Fig. 2 illustrates the operational phase of DeMo. Upon entering an MTR station entrance, delivery workers receive our sensors from MTR staff and attach them to their trolleys, which are loaded with supplies for various shops. During the delivery, workers manually drive the trolleys while DeMo continuously monitors their activities. Specifically, DeMo calculates the trolley's moving speed (Section V-A) using IMU readings and generates the trajectory (Section V-B) by employing a particle filter that integrates BLE packet data and estimated speed. Although the idea seems straightforward, DeMo needs to overcome several unique challenges in MTR stations, such as large errors due to MTR's special road surfaces and missing directions in a severe electromagnetic environment. Based on the estimated speed and trajectory, DeMo performs violation detection (Section V-D).

When arriving at the target store, delivery workers unload their goods, which usually takes 5–20 minutes. DeMo leverages this opportunity to identify the specific store (Section V-C) and mitigate the possible false alarms by analyzing the historical IMU and BLE data. Then, DeMo uploads the delivery record to the server which analyzes the daily violation rate to identify abnormally high violations. Finally, when delivery workers exit the MTR station, they return DeMo's sensors to MTR staff.

IV. Offline Preparatory Phase

Signal Choice: Various signals, such as acoustics, WiFi, camera images, and visible light, have been used for indoor localization. DeMo leverages the RSSI of BLE packets and IMU readings because of the following reasons:

• *Privacy concerns:* Privacy issues restrict us from installing privacy-intrusive devices, such as cameras or depth cameras.

• *Power constraints:* As required by MTR stations, we are only allowed to install small battery-powered devices and prohibit the installation of power cables. Consequently, power-hungry devices like WiFi access points are infeasible. MTR stations also have limited WiFi coverage and require dedicated WiFi access points for WiFi-based localization.

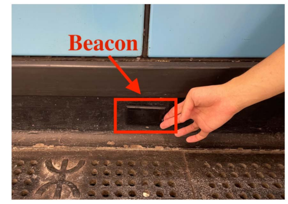

Fig. 4. Sender: A beacon deployed on the skirting board.

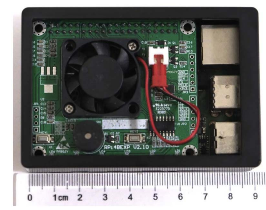

Fig. 5. Receiver: Raspberry Pi 4B and customized HAT.

• *Practicality:* Acoustic-based localization is unreliable in noisy, crowded environments [14], while light-based systems are disrupted by obstructions and lighting changes, making both impractical for dynamic settings like MTR stations.

• *Efficiency:* DeMo achieves desired violation detection based on BLE and IMU with low deployment and maintenance costs.

Sensor Design: This subsection focuses on the hardware design of the sensor, which is different from smartphones in conventional indoor localization systems. We customize on-trolley sensors with two major components, Raspberry Pi 4B and customized hardware attached on top (HAT) in Fig. 5. Our HAT contains an inertial measurement unit (IMU) MPU9250, a speaker for alarm, 6 indicator lights to indicate the operation statuses, and a fan for cooling.

Our sensor captures BLE packets through a Bluetooth chipset, facilitating real-time detection of violations. Upon detecting a violation, it alarms via a speaker and also reports to the server using a 4G dongle. Given that the report comprises solely essential information, such as sensor ID, station, entry/exit, delivery time, destination shop, and violation type, the energy consumption is moderate. The overall energy consumption for DeMo's sensing, computation, and data uploading approximates 400 mW. We chose the Raspberry Pi to minimize the hardware design workload, while its operating system accounts for the majority of the energy consumption (2000 mW). Our sensor is connected to a portable power bank of small capacity, which is recharged approximately every 2 days.

BLE Beacon Deployment: MTR stations enforce strict aesthetic constraints on the deployment of BLE beacons. We utilize small-size, battery-operated, and black-coated beacons, installing them at skirting board locations (Fig. 4) close to the ground. The inter-beacon distance ranges from 6 to 8 meters in the majority of areas. During the initial trials of DeMo, we identified several areas prone to significant errors or critical to DeMo's operation. This observation led us to implement specialized deployment strategies for these zones. In the case of

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TABLE IV
BEACON TYPE COMPARISON

Comparison	Type 1	Type 2
Appearance		
Size	39x39x15mm	86x54x6mm
Cost	6.3 USD	9 USD

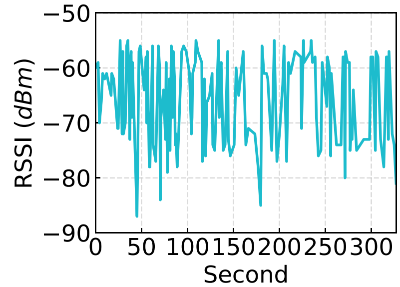

Fig. 6. Abrupt RSSI change with time at a static sensor.

large pillars, beacons are deployed on all four sides to mitigate signal obstruction. For in-station stores, we deploy 3 beacons (two externally and one internally) to improve the store detection accuracy.

During the operation of DeMo, we found the beacon types impact our maintenance. Table IV presents two types of beacons primarily utilized in DeMo. In the initial stations, beacon type 1 was deployed, but a significant loss rate of 9% was observed after five months (Section VI-E). This loss was attributed to the high chances of collisions with passengers. To reduce maintenance costs, we switched to beacon type 2. The card-shaped design offers larger adhesive contact areas and minimizes collision probability with walking passengers, resulting in enhanced reliability—approximately 2.3% loss rate after five months. This motivates us to deploy only beacon type 2 in later deployment/maintenance. Overall, we have deployed DeMo in 12 MTR stations with over 1,500 beacons.

RSSI-Distance Model Verification: Many localization systems [12], [25], [26], [38], [74] rely on radio fingerprinting for accurate localization and require intensive deployment costs. Although RSSI-distance models have been extensively discussed in the literature for localization in small-scale indoor scenarios for alleviating deployment efforts [5], [7], [15], [39], [54], its verification is fundamentally missing in large-scale settings. In contrast, DeMo adopts a low-cost and accurate RSSI-distance model for large-scale operation.

We started with classic free-space propagation models, e.g., the well-known logarithmic model $r = r_0 + 10N \log d + X_\sigma$ [54]. Our initial trials brought up multiple unique challenges in complex MTR stations. (1) Crowd obstruction and reflection. These factors lead to signal losses that deviate from the logarithmic model, which is especially inaccurate under weak RSSI. (2) Highly dynamic crowd movement. The complex MTR environment results in abrupt RSSI changes even when our sensor is static. Fig. 6 shows an example of the RSSI change with time at a static sensor - directly adopting a propagation model will lead to significant localization errors. In addition to the logarithmic model, we also tried multiple fine-tuned RSSI-distance models (e.g., [5], [7], [15]) but noticed more severe localization errors caused by the complex and dynamic MTR environment.

These preliminary tests motivate us with the following reliable model applicable to complex and dynamic settings. First, we transfer the logarithmic model to a probability distribution model to be used in a particle filter: $p(r|d) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{1}{2\sigma^2}(r - \hat{r})^2)$, which represents the conditional probability of receiving an RSSI value r given a distance d, where $\hat{r} = r_0 + 10N \log d$. This probability follows a Gaussian distribution with mean $\hat{r}$ and variance σ^2. Next, to combat crowd reflection and obstruction, we ignore weak RSSI values under a threshold (empirically set to -80 dBm) to only leverage strong signals with good reliability. We also modify the probability model as follows: $p(r|d) = k \exp(-\frac{1}{2\sigma^2}(r - L(\hat{r}))^2)$, where $L(\hat{r}) = \gamma_0 + \gamma_1\hat{r} + \gamma_2\hat{r}^2 + \gamma_3\hat{r}^3$ is a cubic polynomial function to model crowds' impacts and k is adjusted normalization. We have tried multiple polynomial functions and observed that our current cubic function provides good accuracy while maintaining reliable generalization. Higher or lower-order polynomials commonly encounter larger errors when applied across different MTR stations. A detailed comparison is included in Section VII-D. Coefficients (e.g., γ_0, γ_1, γ_2, and γ_3) are determined through simulation experiments, and our detailed training procedure is open-sourced at [19]. To mitigate the highly dynamic crowds, DeMo adopts a sliding window of 4 seconds and leverages the maximum RSSI within this period, which outperforms other statistics, e.g., the average, median, or the most recent RSSI value. This sliding window enhances DeMo's reliability against lost BLE beacons while its duration is empirically set to 4 seconds to ensure the balance between reliability and delay. A short window might suffer from insufficient BLE packets, while a long window leads to a larger delay.

Our training data is collected in three representative areas (e.g., MTR's entrance, store area, and corridors) and consists of RSSI values collected at different distances from our beacons to sensors. The entire data collection process takes approximately one hour for a single staff. In contrast, fingerprinting-based methods typically require exhaustive signal surveys. For environments of 50 K-100 K m^2, it may take 28 to 56 hours for a human surveyor to complete data collection [38]. Despite using a model-driven approach, the overall mean localization error solely based on BLE without IMU (Section VII-D) is 2.81 m. We further validate our model across the remaining stations without parameter retraining. Detailed results are included in Section VII-D. In most stations, the positioning error is similar to our initial station used for model training, ranging between 2.42 m and 3.39 m. Nevertheless, two subway stations suffer from more significant positioning errors at 3.68 m and 3.83 m. These two stations boast unique layouts featuring larger open spaces, unlike most subway stations that have long, narrow delivery areas. In addition, we observed more severe beacon

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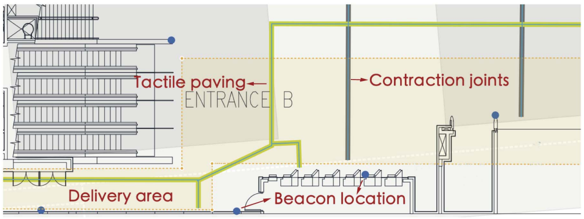

Fig. 7. Pre-processed floor plan. Yellow regions represent designated delivery areas.

(a) Tactile paving (b) Contraction joints (c) Normal road

Fig. 8. Examples of different road surfaces: tactile paving, contraction joints, and a normal road.

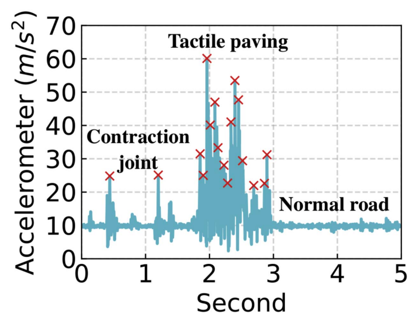

Fig. 9. IMU readings at different surfaces.

damages in these two stations. These factors result in diminished positioning accuracy. These experiments verify the feasibility of low-cost and accurate localization based on a simple RSSI propagation model - one-time training is adequate for accurate localization in complex environments like HK's MTR stations. Transferring our model to other scenarios (e.g., subway stations located in other cities) involves parameter reconfiguration, while we have open-sourced our parameter configuration procedures at [19].

■ *Finding 1: Without labor-intensive site surveys, a well-customized RSSI model offers accurate localization in complex and dynamic indoor environments like MTR stations. The deployment cost could be reduced by one-time parameter tuning and adoption to all stations with similar accuracy.*

Floor Plan Processing: We enhance the floor plans of MTR stations with detailed information, including geo-fencing [63] and surface statuses. Geo-fencing involves adding polygons to the floor map to demarcate the delivery area in compliance with MTR regulations. These polygons are then utilized during the online phase for violation detection. Additionally, geo-fencing delineates store areas to trigger the delivery destination recognition module. We also the ground surface conditions of MTR stations. During our preliminary deployment, we noticed that certain road surfaces (tactile paving and contraction joints) lead to special patterns on the IMU readings, which could be leveraged for improving detection performance (further details in Section V-A). Note that DeMo avoids tedious examination of each station since MTR stations' surfaces follow specific construction regulations and exhibit very similar IMU patterns. Fig. 7 shows an example of the pre-processed floor plan.

V. Online Operational Phase

A. Online Speed Detection

DeMo estimates the trolley's real-time speed by analyzing IMU readings through two components: road surface detection and speed calculation. Special road surfaces cause substantial IMU fluctuations, resulting in significant integral errors. Consequently, in the speed calculation process, we exclude IMU readings caused by these surfaces to maintain speed accuracy.

Road Surface Detection: Special road surfaces (tactile paving [60] and contraction joints [41]) lead to large IMU fluctuations and speed estimation errors when a trolley passes these surfaces. Specifically, tactile pavings (Fig. 8(a)) consist of 4 parallel bars and are widely used to assist pedestrians with vision impairment. Contraction joints (Fig. 8(b)) have a narrow width and are often used to avoid cracking damage caused by thermal expansion. This motivates us to detect these special surfaces to improve speed detection accuracy.

Fig. 9 compares the IMU readings when a trolley passes different surfaces. We observed that the IMU readings fluctuate for a short period of time when passing through the tactile paving. Similarly, passing through the contraction joint presents large fluctuations but at a shorter duration. These large IMU fluctuations inspire us to adopt peak detection [59] to recognize road surfaces. Specifically, we calculate the standard deviation of the IMU denoted as a_{std} and extract peak values that are at least 4 times the standard deviation. The time interval between sequential peaks is denoted as $t_1 \ldots t_n$, with n number of peaks. Considering that tactile paving contains 4 parallel bars and a trolley's typical movement speed, DeMo's tries to detect $n = 8$ peaks within a short interval threshold (e.g., 0.04 s to 0.2 s). If the above two conditions hold, the surface is recognized as tactile paving. DeMo adopts a similar strategy to detect a contraction joint, if n is 2 and each of $t_1 \ldots t_n$ is between 0.2 and 1 s. The value of n considers the characteristics of the specific road surface (e.g., 4 parallel bars) and the number of times the delivery wheel has passed.

Speed Calculation: To offer accurate speed detection, DeMo analyzes IMU readings with the following procedures.

• *Sensor status detection:* When the a_{std} is under 0.01 g [62], the sensor is considered to be static; it is moving otherwise.

• *Sensor placement detection:* In practice, delivery workers adopt the following placement: 1) Our sensor is in a pocket or hand. Traditional pedestrian dead reckoning methods [29], [42], [62] can be used to recognize human walking patterns like step detection for speed inference, as widely discussed in literature [38], [61], [67]. 2) Our sensor is placed on a trolley.

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DeMo identifies this placement if IMU readings lack human walking patterns [8]. Based on DeMo's operational results (Section VI-C), our sensor is placed on trolleys for 95% of deliveries.

• *Adaptive integral of IMU readings:* For an on-trolley sensor,[2] DeMo estimates this trolley's speed by analyzing IMU readings. First, DeMo removes noises and outliers through a low pass filter, excluding IMU readings that resulted from special road surfaces. Second, DeMo detects acceleration and deceleration by analyzing the IMU distribution. According to our practical experience, the accelerometer readings are dominated ($>80\%$) by either positive or negative values when the trolley accelerates or decelerates. Once identifying these phenomena, DeMo integrates IMU readings with the previous speed to re-estimate the current speed. Otherwise, when a sensor is considered to have uniform movement, DeMo does not re-estimate the current speed.

■ *Finding 2: Identification of road surfaces (e.g., tactile paving and contraction joints) via IMU processing benefits speed estimation accuracy:*

B. Online Positioning

Floor Detection: Prior to online localization, DeMo first determines the floor level. Floor estimation relies solely on BLE RSSI signals. DeMo employs a straightforward algorithm for floor detection. This algorithm executes a majority voting mechanism based on the six most potent BLE beacon signals received within a 4-second interval. It is important to note that the floor detection algorithm does not operate continuously. When an anomalous variation in the accelerometer's readings is detected, the floor detection algorithm will be reactivated.

Online Localization: DeMo leverages a particle filter (PF) [23] to recursively update the probability distribution for tracking the trolley position in real time. We choose PF because it is good at fusing diverse signal sources (e.g., BLE, IMU) and also offers good reliability with less training data in dynamic situations.

For initialization, DeMo generates N particles with equal weights, evenly distributed across the delivery area. The number of particles significantly impacts localization accuracy and computational efficiency. While increasing the particle count improves positioning accuracy, the gains diminish beyond a certain point, with higher computational costs affecting real-time performance. We empirically selected N in the range of 500 to 800, depending on the size of the delivery area. In each iteration, DeMo moves its particles through the transition model and updates particle weights accordingly. To tackle the missing movement direction, DeMo leverages IMU readings and the trolley's historical trajectory to estimate the moving direction. Specifically, we combine the accelerometer and gyroscope readings to calculate the Euler angle [20] and move each particle to a new position based on the variance of the yaw angle and the speed produced from Section V-A. In practice, we observe a high variance of the yaw angle when the trolley turns, while the variance is small when moving in a straight line. As a result, when the yaw angle's variance is small, most particles maintain the previous motion direction, while a small number of particles follow a uniform distribution to simulate random movement. Otherwise, the number of particles with random movement increases to estimate the new movement direction. When receiving a BLE packet, DeMo updates its particle weights via our RSSI-distance model (Section IV). After the above updates, DeMo finds a center point of the top p_w weighted particles and repeats this iteration with new BLE+IMU readings. p_w is empirically set to 60%.

[2] For in-hand or in-pocket sensor, DeMo leverages existing techniques for speed estimation [42].

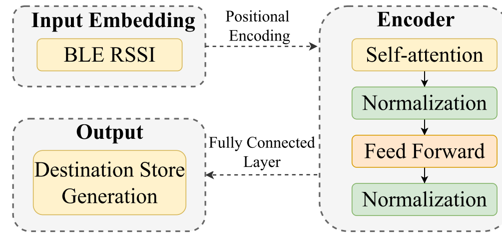

Fig. 10. Destination store identification with BLE-Former.

C. Destination Store Identification

Store identification is triggered when a delivery trolley enters the store area and is then stopped by the delivery worker for supply uploading. A direct approach is to infer the destination shop by comparing positioning results to stores' locations on the map. Although this approach is effective for stores with broad storefronts (e.g., $>$ 6m), it is insufficient to accurately determine the intended delivery destination for narrow stores, which account for 54% of the total stores. To address this issue, DeMo integrates a transformer-based algorithm tailored for store identification.

Intuitively, BLE RSSI values are sequence data, which are appropriate for sequence-based neural networks, such as Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models [34]. RNN and LSTM have been widely studied for sequential data analysis across various domains, such as machine translation [78], handwriting recognition [49], and mobile applications [86]. While these models have demonstrated great performance, they are not designed to model sequences where elements in sequences are of diverse importance, e.g., RSSI from different beacons. In contrast, the transformer model [73] is designed for modeling elements with diverse importance by the self-attention mechanism, which suits our BLE RSSI data. Moreover, Transformer-based models have achieved superior performance in multiple mobile sensing applications [31], [35]. Therefore, we design BLE-Former, a transformer-based model for modeling multi-channel BLE RSSI signals, which is tailored with significant cost reduction for practical delivery monitoring.

Our BLE-Former adopts an encoder-only architecture to analyze BLE RSSI captured by sensors on delivery trolleys, which simplifies the model structure and reduces computation by removing the decoder module. Fig. 10 illustrates the key

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components of BLE-Former, i.e., BLE Signal Embedding, BLE Signal Encoder, and Destination Store Generation.

• *BLE Signal Embedding:* In each time window, our sensor receives consecutive BLE signals from multiple surrounding beacons, which consist of beacon IDs and corresponding RSSIs. Initially, beacon IDs are transformed into dense vector representations through an embedding process. These vectors are subsequently concatenated with their respective RSSI values, forming a multi-channel input embedding $\mathtt{Emb}_{\mathtt{BLE}}$, representing the semantics of the current location.

• *BLE Signal Encoder:* Then, the encoder layer further transforms the signal embedding for final store identification. Our encoder layer consists of self-attention, layer normalization, and feedforward layers. Specifically, $\mathtt{Emb}_{\mathtt{BLE}}$ first goes through a self-attention layer, which is followed by a normalization layer to stabilize the training process. Given the diverse importance of beacons, the self-attention layer identifies the important ones for store identification automatically. Then, a feed-forward neural network and another normalization layer are concatenated. Also, to preserve the temporal pattern of signal strengths from different beacons, positional encodings are integrated with the input features, which is essential for our model to capture the chronological order of beacon signals.

• *Destination Store Generation:* At the output stage, a fully connected layer with a softmax activation function is utilized to predict the probability distribution over the potential destination stores. The store with the highest probability will be identified as the trolley's final destination based on the observed RSSI patterns.

• *Implementation:* In practice, stations have different stores with diverse beacon distributions. Therefore, for each station, we train a BLE-Former model to predict a one-hot encoded vector representing the target store. The target store labels are collected from several hired delivery personnel. After the training process, our model was deployed on-trolley sensors. Compared to the basic store identification approach, BLE-Former can significantly increase the identification accuracy with acceptable energy consumption (Fig. 16 in Section VI-D).

D. Operational Model

Targeting violation detection and safe delivery, DeMo has the following designs.

Real-Time Violation Detection: To satisfy the requirement of real-time operation, DeMo's computation is placed on the sensor (Raspberry Pi) side. This also avoids significant delay and energy consumption for data uploaded to the cloud server. For speed violations, DeMo compares the speed calculated in Section V-A with the regulation (1.5 m/s) to detect if there is a speed violation. Then DeMo leverages the positioning results calculated in Section V-B for delivery trajectory generation. By checking allowed delivery areas, DeMo is able to detect delivery involving non-designated path/entrance/exit. For passenger lift violation, DeMo first utilizes IMU and BLE readings to recognize the floor change via lifts and then checks the current position with the map to identify passenger lifts. As for the detection of peak-hour delivery, our on-trolley sensors record the delivery

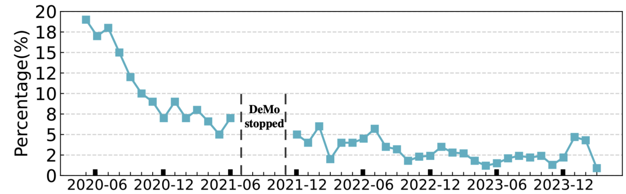

Fig. 11. Violation (speeding) rate.

start time and end time for checking with peak hours (7:00-10:00 am and 4:00-8:00 pm). If a violation is detected, DeMo alarms the delivery worker through its speaker immediately to correct his/her delivery behavior.

Daily Report: When a delivery worker arrives at the target shop, this delivery worker stops his/her trolley for supply unloading, which will usually last 5–20 minutes. DeMo leverages this opportunity to process historical IMU+BLE data to mitigate false alarms and identify the destination shop based on positioning results and IMU patterns. Then DeMo generates the current delivery record that logs the DeMo sensor ID, entry/exit, destination shop, delivery time, and the delivery violation type. After this, DeMo uploads the current delivery record to our cloud server via a 4G dongle. Due to a delivery record's limited size, this record uploading requires tiny energy consumption. DeMo's server processes these records to generate daily reports for MTR.

VI. Large-Scale Operation

This section offers DeMo's large-scale in-the-wild operation results. DeMo covers more than 200 shops at 12 MTR stations with a delivery area of 19,433 m^2. Since its debut in May 2020, DeMo has monitored 74,537 deliveries with a 6193.2 km delivery length. By default, the beacons have a broadcast interval of 200 ms, and the sample rate of IMU is 500 Hz.

A. Violation Behavior Analysis

Violation Reduction: For each violation type, its violation rate is calculated as the number of violations divided by the total number of deliveries for all stations. According to DeMo, the violation rate for wrong delivery path, delivery in peak hours, and using passenger lifts was 1% in 2020 and dropped to 0.3% in 2024. Fig. 11 shows DeMo's detection results of speeding violations.[3] At first, DeMo detected a high violation rate of around 19%, meaning that almost one-fifth of the delivery is speeding with potential safety risks to commuters. Targeting safe delivery, DeMo offers accurate violation detection (more details in Section VII-B) and generates alarm warnings in real time. These real-time alarms effectively correct workers' delivery behaviors, e.g., slowing down the movement speed. By doing so, DeMo gradually reduced the violation rate with time, which reached 0.9% in March 2024.

Prior to DeMo, MTR stations also adopted a manual monitoring system for many years without such an achievement.

[3]Due to the COVID-19 outbreak, DeMo was suspended at MTR stations from July 2021 to November 2021.

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TABLE V
A/B TESTING

Station	Version A Violation Rate	Version B Violation Rate
Station 1	3.61%	9.22%
Station 2	5.19%	11.51%

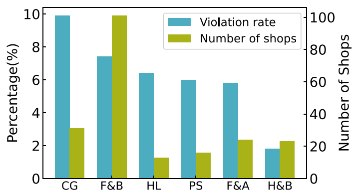

Fig. 12. Distribution of violation shops.

Given that DeMo effectively monitors more than 91% of the total delivery events,[4] DeMo offers effective correction on delivery behaviors with enhanced safety protection.

A/B Testing: To exclude the placebo effect, we launched additional A/B testing to analyze DeMo's influence on delivery behaviors. This test was conducted in two MTR stations for two months. Version A was the operational DeMo discussed in Section III-C and was tested in the first month. In the second month, we tested Version B, which had all the same components (e.g., speeding violation threshold and daily report generation) as Version A, while the only exception was that the real-time alarm notification was disabled. Delivery workers were not informed of this change. This also rules out delivery workers' perception of our devices since the *alarming function* is the only difference between Version A and B. Table V shows the comparison of violation rates. Note that we have only detected the speeding violations, and no other types of violations were detected during these two months. The violation rate increased in both of these two stations, demonstrating the critical role of real-time alarms in notifying delivery workers of behavior changes.

■ *Lesson 1: DeMo's 4-year large-scale operation effectively reduces the violation rate from 19% to 0.9%. As indicated by our A/B test, accurate violation detection and real-time warning are necessary prerequisites for such a positive delivery behavior change.*

Shop Category's Impacts: We classify more than 200 shops in MTR stations as convenience goods (CG), food and beverage (F&B), fashion and accessories (F&A), health and beauty (H&B), home living (HL), and passenger services (PS). For each shop category, the violation ratio is counted as the number of violations divided by the total delivery, as demonstrated in Fig. 12. Overall, the CG category has the highest violation rate, followed by the F&B category. This is likely because these stores have a high demand for replenishment that naturally leads to more incentives for delivery workers to expedite deliveries.

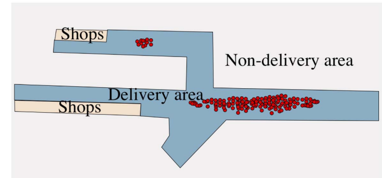

Fig. 13. Speeding event locations.

Geographic Distribution: We observed that certain areas, such as long (more than 20 m) and wide (5 m or more) corridors, exhibit much higher chances of speeding. Generally, speeding violations often occur in the middle of straight roads to the shops. This suggests that MTR stations take specific countermeasures to improve safety. Fig. 13 shows one example of the clustered violation distribution, where each dot represents a speeding violation.

B. DeMo Versus Manual Monitoring

Compared with manual monitoring/recording via hired MTR staff,[5] DeMo has the following unique advantages.

- *Full coverage of violation detection:* DeMo reliably detects 4 types of violations, while manual monitoring is not well suited for speeding detection.
- *Delivery behavior change:* DeMo regulates delivery behaviors with corrections and reduces the violation rate from 19% to 0.9% as demonstrated in Section VI-A, which is fundamentally missing in the manual system.
- *Efficiency:* Manual monitoring requires a safety staff for each delivery with intensive human resource requirements. In contrast, DeMo successfully monitors 74,537 deliveries, covering 91% of the total delivery activities on average, much better than the 53% monitoring rate offered in manual monitoring. The missing cases are primarily due to insufficient sensors at some stations and sensor hardware failures caused by rough handling.
- *Cost saving:* DeMo's cost consists of one-time deployment and maintenance costs. Its deployment cost includes hardware cost, floor plan processing, beacon installation, and program development. For the hardware cost, DeMo requires Raspberry Pi with HAT (90 USD each) and beacons (9 USD each).[6] Each station needs 5-15 Raspberry Pi and 50-250 beacons, depending on delivery area size. Overall, the one-time deployment cost is about 15K-20 K USD per station. DeMo's maintenance cost to replace failed beacons is about 40 USD per station/month, thanks to DeMo's low maintenance requirement. As for manual monitoring, each station hires multiple safety staff (e.g., 2) depending on the station size. Due to privacy issues, we do not know the exact wage and use the median monthly wage (2,383 USD) in the statistical reports [56]. After DeMo's 4-year

[4]MTR corporation has a record of all delivery activities since shops are mandatory to submit their delivery applications. This record is used as the ground truth to evaluate DeMo's monitoring efficiency. 91% is the number of deliveries detected by DeMo divided by the total number of delivery records according to MTR. The previous manual monitoring only covers 53% of all deliveries due to its intensive human resource requirement and limited staff.

[5]Manual records include violation type, start time, station code, entry/exit, and the destination shop. Note that the records are taken for both violation and non-violation deliveries.

[6]The prices were in 2020.

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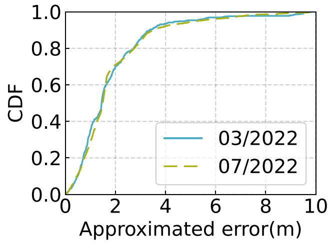

Fig. 14. Approximated positioning error in 2022.

operation, the cost of manual monitoring is at least 10X higher than DeMo.

■ *Finding 3: DeMo outperforms manual services in terms of violation detection coverage (especially speeding detection), delivery behavior change (violation rate drops from 19% to 0.9%), monitoring efficiency (DeMo detects 91% of the total delivery events in contrast to the prior 53%), and cost reduction* ($> 10X$).

C. System Performance

Approximated Positioning Accuracy: In DeMo's large-scale operation, we lack the trolley's ground-truth position. To alleviate this limitation, we utilize the events when trolleys pass tactile pavings to *approximately* evaluate the positioning accuracy since these events could be reliably detected. We adopt the following methodology. IMU readings analysis offers the time T when a trolley reaches tactile paving. We compute the shortest distance from DeMo's current positioning result to the nearest segment of tactile paving. This shortest distance is leveraged as an approximated error, not the *exact* localization error.

Fig. 14 plots the approximated positioning error distribution in March 2022, with a median error of 1.45 m. Furthermore, we evaluate DeMo's stability with time by comparing the approximated error in March and July 2022. After four months, the median positioning error slightly increases to 1.49 m. Note that this approximated error differs from the actual localization error offered from our controlled experiments in Section VII-D.

Statistics of Sensor Placement: We observe that a small percentage of delivery personnel (5%) hold the sensor in their hands or pockets, while the other 95% place sensors on trolleys. DeMo is compatible with both placements.

D. Store Identification Performance

To evaluate DeMo's store identification reliability, we utilize the ground truth provided by the MTR Corporation. Each time a delivery worker arrives at the entrance of an MTR station, an MTR staff distributes DeMo's sensor to the worker and also records the sensor ID along with the destination store ID. This procedure establishes the ground truth for our evaluation. This evaluation spanned one month across 12 stations, involving 3,135 deliveries in March 2023. Our store identification model was trained on a system equipped with an NVDIA GeForce RTX 3050 GPU and 16 GB memory. The implementation utilized Python 3.12. The training process spanned 200 epochs with a learning rate of 0.001. After the training procedure, our model was subsequently deployed on a Raspberry Pi device to validate its real-time feasibility and adequate energy consumption. The Raspberry Pi operated on Raspberry Pi OS Lite and was configured with 2 GB of RAM.

Store Identification Accuracy: We compare DeMo with the following baselines for store identification accuracy.

- *Positioning-based store identification (Pos-based):* This method infers the destination store based on the trolley's positioning results when it stops for unloading.
- *XGBoost:* Extreme Gradient Boosting (XGBoost) [11] is one of the traditional classification models, which is a scalable tree boosting system with a large number of decision trees to learn functions sequentially.
- *LightGBM:* Light Gradient Boosting Machine (LightGBM) [16] is a fast, efficient, and scalable gradient boosting framework that uses tree-based learning algorithms for high-performance machine learning tasks.
- *LSTM:* Long Short-Term Memory (LSTM) [34] is a type of RNN architecture designed to recognize patterns in sequences of data, with enhanced memory capabilities for capturing long-term dependencies.

The store identification accuracy results are shown in Fig. 16. The XGBoost model achieved an accuracy of 85.2%, while the positioning-based method slightly outperformed it with 87.7%. Despite DeMo's reliable positioning, identifying the correct store remains difficult due to the narrow storefronts. The LightGBM model achieved a higher accuracy of 88.1%. Leveraging its ability to capture long-term dependencies, the LSTM model further improved accuracy to 93.1%. In contrast, DeMo outperforms these baselines with an accuracy of 97.8%. This demonstrates that DeMo's BLE-Former technique can markedly enhance store location pinpointing, boosting the operation reliability. In addition, the power consumption of DeMo's BLE-Former module is 85.7 mW. This energy consumption could be further reduced by utilizing the IMU readings to turn on DeMo's BLE-Former module upon detecting IMU fluctuations caused by trolley movement.

■ *Finding 4: In the challenging context of narrow storefronts within MTR stations, the simple architecture of the encoder-only transformer model ensures accurate and reliable store identification performance with low computational costs.*

Impact of RSSI Thresholds: The RSSI threshold enables effective noise filtering from RSSI signals and serves as a critical hyperparameter in our transformer-based algorithm for store identification. To evaluate its impacts, we have delineated the correlation between RSSI readings and store identification accuracy, as depicted in Fig. 17. Empirical analysis has determined the optimal RSSI threshold to be 81 dBm, with the highest identification accuracy. Configuring the RSSI threshold above this optimal point leads to dropping useful signals, thereby diminishing the system's precision. On the contrary, a low threshold admits weak signals, which exhibit diminished sensitivity to distance variations, thus introducing an increased level of noise into the predictive model.

BLE Beacon Deployment Strategies: DeMo leverages three BLE beacons deployed in the store (two outside and one inside the store) for store identification. To validate this deployment

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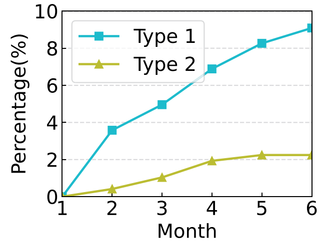

Fig. 15. Beacon failure rate with time in 2020.

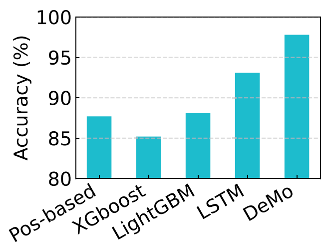

Fig. 16. Store identification accuracy comparison.

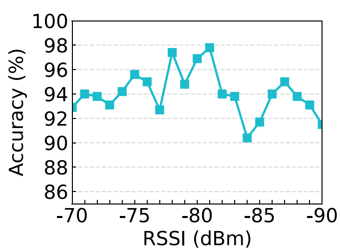

Fig. 17. RSSI thresholds versus store identification accuracy.

TABLE VI
COMPARISON OF IN-STORE BEACON DEPLOYMENT STRATEGIES VERSUS STORE IDENTIFICATION ACCURACY

# of beacons	3	2(L-R)	2(L-I)	2(R-I)	1(L)	1(R)	1(I)
Accuracy(%)	97.8	82	75	89.5	72.7	86	87.2

The notation used to describe the number and position of beacons includes "L" for left, "R" for right, and "I" for inside. For instance, "2 (L-R)" denotes the deployment of two beacons positioned at the left and right sides of the store.

choice, this study compares the performance of store identification accuracy across configurations of three, two, and one beacon(s) deployed within the store premises. Temporary deactivation of selected beacons was implemented between the BLE-Former training and testing phases. Detailed result is shown in Table VI, we observe considerable accuracy differences across different deployment strategies. As shown, deploying either two or one beacon(s) significantly reduces the accuracy, ranging from 75% to 89.5%. In contrast, the deployment of all three beacons yields an accuracy of 97.8%, demonstrating its reliability in the wild.

E. System Maintenance

This section provides an analysis of DeMo's maintenance costs, focusing on the impact of beacon types and the location of beacon failures.

TABLE VII
BEACON FAILURE AT DIFFERENT LOCATIONS

Location	Store	Entry/Exit	Corridor	Others
Failure rate (%)	5.3	3	1	0.6

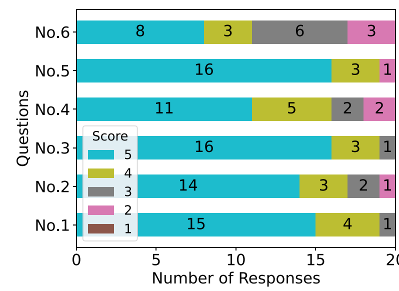

Fig. 18. Feedback from 20 MTR staff.

Impact of Beacon Types: Recall from Section IV, we choose two types of beacons called type 1 and type 2 for our deployment. Initially, we adopted type 1 beacons but observed a high loss rate due to various factors, such as natural falls and collisions with passengers. This high loss rate motivated us to switch to type 2 beacons in subsequent deployments and maintenance, as discussed in Section IV. Fig. 15 illustrates the beacon failure rate over time. After 5 months, the loss rate for type 1 beacons reached 9%, while type 2 beacons exhibited a much lower loss rate of around 2.3%. This experiment demonstrates that selecting appropriate beacons can effectively reduce maintenance costs.

Failed Beacon Locations: Table VII presents the beacon loss rate at different locations. These statistics only include beacon type 2 and were collected 5 months after the deployment. Areas such as stores and entry/exit exhibit the highest beacon loss rates, likely due to the dense crowds in these locations. For locations with high loss rates, we increase the beacon broadcast frequency (e.g., 100 ms) to compensate for lost beacons and maximize the utility of the beacons before they fail.

■ *Finding 5: Strategic beacon deployment could alleviate system maintenance costs. For example, card shape beacon (type 2) significantly reduces the beacon failure rate compared with common box-shaped beacons. As a result, beacon shape and deployment areas should be thoroughly considered, while beacon broadcast frequency in high loss-rate areas could be increased for better utilization before device failures.*

F. MTR Feedback

We designed a questionnaire to evaluate DeMo's performance and Fig. 18 depicts the feedback from 20 safety staff in 12 MTR stations. Our survey contains six questions, each employing a 5-point Likert scale ranging from 5 (strongly agree) to 1 (strongly disagree). The six questions are: 1. please indicate your level of satisfaction with the DeMo, 2. please assess the ease of use of the DeMo's device, 3. please evaluate the effectiveness of the DeMo in reducing delivery violations, 4. please rate the accuracy of the DeMo in speed detection, 5. please describe the impact of the DeMo on reducing your workload, and 6. please indicate the frequency of sensor damage encountered with the DeMo.

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Overall, DeMo receives positive feedback from the majority of MTR staff. Taking question 1 (satisfaction with our system) for example, more than 95% of the interviewees highly rate DeMo with a score of 4 or 5 (strongly agree). We summarize these questions with four takeaway messages.

(1) User friendly: The operation of DeMo is easy and convenient without complicated knowledge. The sensor is simple and does not require additional learning costs to get used to the sensor. What's more, the use of the sensor will not cause inconvenience to the delivery personnel during the delivery process and will not interfere with their normal delivery.

(2) Violation rate decrease: DeMo effectively decreases the violation rate by correcting delivery behaviors. Upon detecting a violation, DeMo alerts the delivery personnel through an alarm via the embedded speaker. Such alerts can effectively change the behavior of delivery personnel.

(3) Workload reduction: Prior to the operation of DeMo, stations' safety staff were required to accompany delivery trolleys to oversee the delivery process and manually record any violations. Moreover, in assessing speeding, it is difficult for station staff to have a unified standard only based on personal feelings. Upon deployment, DeMo can autonomously monitor the status of trolley deliveries and identify violations, effectively reducing MTR staff's workload.

(4) Sensor failure: Some interviewees complained about sensor failure caused by delivery workers' rough handling (about one device/month in some stations). Our device was not designed with industry-level reliability and could be damaged by collision, which needs to be improved in the future.

■ *Finding 6: DeMo is highly rated by the majority (95%) of MTR operators. Its positive feedback covers various aspects, such as easy accessibility, effective delivery behavior change, and workload reduction. On the other hand, we plan to address device failures by designing more reliable hardware.*

VII. Evaluation via Controlled Experiments

This section evaluates DeMo via controlled experiments with collected ground truths, in contrast to our large-scale in-the-wild evaluation in Section VI. Our controlled experiments last 15 days and cover 0.9 k delivery cases with a total length of approximately 54 km.

A. Evaluation Methodology

Without loss of generality, we chose three stations of different scales (552, 1105, and 3,003 m^2 respectively) to represent small, medium, and large stations for our controlled experiments. We hired several delivery personnel to perform test deliveries in each station, while DeMo operated in real-time to monitor all the delivery procedures. To evaluate DeMo, we adopt the following ground truth collection mechanisms instead of leveraging in-the-wild deployment data. In this evaluation, our testing device has an embedded screen that displays the MTR floor map with special *checkpoints* that could be easily found (e.g., pavement contraction joint, pillar, lift). The distance between the two checkpoints is about 5 m. When passing through a checkpoint, hired delivery personnel will click on the screen to record the ground-truth location and time. The ground-truth speed of two adjacent checkpoints can be calculated accordingly.

TABLE VIII
Violation Detection Accuracy

Violation Type	TP (%)	TN (%)	FP (%)	FN (%)
Speeding (real-time)	95.1	83.7	16.3	4.9
Speeding (daily report)	97.6	90.7	9.3	2.4
Wrong delivery path	100	100	0	0
Using passenger lift	100	100	0	0
In peak hour	100	100	0	0

For violation behaviors, hired delivery personnel purposefully violate the delivery rules, such as speeding, delivering during peak hours, using non-designated paths, and using passenger lifts. We have obtained approval from MTR stations and adopted additional safety measures for passenger safety.

B. Violation Detection Reliability

We evaluate DeMo's detection reliability for four violations mentioned in Section II. Overall, our data set contains 900 deliveries. Among them, the number of violations for speeding, wrong delivery paths, taking passenger lifts, and delivery in peak hours is 41, 16, 18, and 11 respectively, with 86 violations in total. Each delivery includes one violation. To ensure a balanced data set, we randomly selected a subset of normal deliveries (without any violation), with the number of 43, 18, 19, and 12, respectively. Table VIII demonstrates the detection performance with the following metrics. True Positive (TP) represents that DeMo correctly identifies a delivery violation. True Negative (TN) indicates the accurate detection of a normal delivery. False Positive (FP) shows DeMo falsely recognizes a normal delivery as a violation. False Negative (FN) means DeMo recognizes a violation as non-violation. Note that only speeding (daily report) in Table VIII is based on the historical IMU+BLE data during the delivery procedure, while all other evaluations are real-time.

For real-time speeding detection, DeMo achieves a TP rate of 95.1% and TN rate of 83.7%, while it suffers from 16.3% FP errors and 4.9% FN errors. When the current speed exceeds 1.5 m/s, the speeding criteria defined by MTR stations, DeMo could reliably detect it as a speeding violation. However, when the current speed is smaller than but close to 1.5 m/s, DeMo might classify this case as speeding, leading to FP results. This is the reason that DeMo's FP is significantly worse than FN, which is deliberately adjusted by us since MTR stations hope to slow down delivery workers to ensure safety. Leveraging historical IMU+BLE data, DeMo manages to further reduce the FP and FN performance.

Besides speeding detection, DeMo offers reliable performance for the remaining 3 violations. Thanks to DeMo's accurate localization performance (a median positioning error of 1.89 m), it is able to generate accurate delivery trajectory by connecting individual positioning results. By checking the current trajectory with allowed areas, DeMo can identify non-designated delivery paths. Since freight lifts and passenger lifts are far away from each other (more than 6 m), DeMo can accurately detect the use of passenger lifts. For each delivery, our on-trolley sensors record the delivery start and end times for checking with peak

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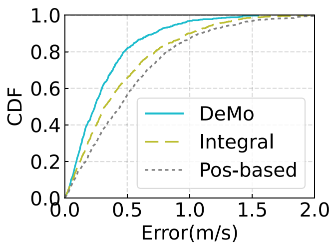

Fig. 19. Trolley speed estimation accuracy.

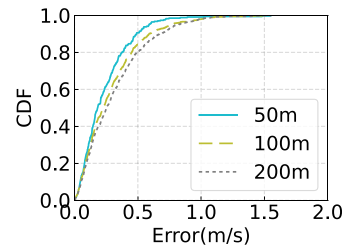

Fig. 20. Delivery path length with speed estimation error.

TABLE IX
DELIVERY PATH LENGTH DISTRIBUTION

Delivery Path	<50 m	50 - 100 m	100 - 200 m
Fraction (%)	10	75	15

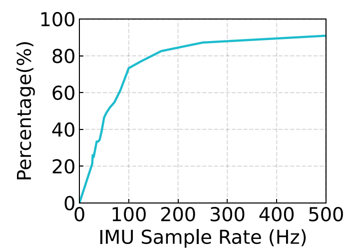

Fig. 21. IMU sample rate versus road bump detection rate.

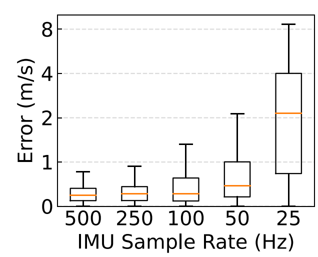

Fig. 22. IMU sample rate versus speed error.

hours (7:00-10:00 am and 4:00-8:00 pm). Given a long delivery duration, e.g., 20 minutes, DeMo ensures accurate detection of peak-hour delivery. Overall, DeMo offers accurate detection for different types of violations in Table VIII, demonstrating its reliability in practice.

■ *Lesson 2: A monitoring system based on low-cost hardware (BLE and IMU) is adequate for reliable (TP > 95% for all required scenarios) and real-time violation detection toward safe delivery.*

C. Speed Detection Performance

Speed Detection Accuracy: We compare three speed calculation methods: the algorithm used in DeMo, the traditional integral method without road surface detection, and a positioning-based approach where speed is calculated from localization results. The ground truth speed is calculated from the ground-truth locations of hired delivery personnel and the times at which they pass these locations.

Fig. 19 illustrates the overall speed detection error. Unsurprisingly, the positioning-based approach results in the highest mean speed error of 0.52 m/s. This is because the localization involves multiple sources of errors, such as wireless fading, failed BLE beacons, and IMU fluctuations. In contrast, directly calculating speed via IMU readings is only affected by IMU errors. For the speed detection based on direct integration, the mean error is 0.43 m/s. DeMo improves its speed detection accuracy by identifying and excluding special road surfaces, resulting in a mean error of 0.31 m/s. The tail improvement is even more significant: the third quartile error decreases from 0.62 m/s to 0.44 m/s, enhancing the reliability of speeding violation detection.

Impact of Delivery Path Length: Table IX shows the distribution of the delivery path length from the station entry to the destination shop. Fig. 20 demonstrates trolley speed estimation errors under the different path lengths of 50 m, 100 m, 200 m. We observe smaller errors for short paths, with a median error of 0.18 m/s for paths less than 50 m. In contrast, long paths (100-200 m) exhibit larger errors, with a median error of 0.23 m/s. This difference is attributed to the accumulation of integral errors over time. Although speed estimation errors accumulate with time, the speed accuracy difference between short ($\sim$ 50 m) and long ($\sim$ 200 m) paths is less than 0.1 m/s, suggesting DeMo's overall reliability.

■ *Finding 7: DeMo detects special road surfaces (e.g., tactile paving and contraction joints) solely based on IMU readings for accurate speed estimation, which reduces 28% of the average speed error compared with conventional integral computation.*

IMU Sample Rate: In this experiment, we set the IMU sample rate to 500 Hz for data collection and then down-sampled it to generate the IMU data at different frequencies. Fig. 21 shows the detection accuracy of road bump events, including tactile paving and contraction joints. Generally, DeMo's detection rate increases with the IMU sample rate and maintains a stable performance at 200 Hz. Similarly in Fig. 22, the speed estimation error is significant when the IMU sample rate is less than 100 Hz. As for energy consumption, increasing the sampling rate from 50 Hz to 500 Hz contributes to less than 3% of the total energy consumption (including sensing and computation). This experiment suggests that a relatively high IMU sample rate is desirable for reliable monitoring.

D. Positioning Performance

Positioning Accuracy: Fig. 23 presents a comparison of the positioning accuracy among several models: the traditional

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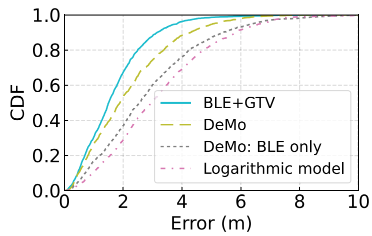

Fig. 23. Positioning accuracy.

TABLE X
POSITIONING ACCURACY IN 12 STATIONS

Station	1	2	3	4	5	6
Accuracy (m)	2.81	2.55	2.93	2.62	2.99	3.39
Station	7	8	9	10	11	12
Accuracy (m)	2.82	2.42	3.68	3.83	2.45	2.51

TABLE XI
MEAN LOCALIZATION ACCURACY UNDER DIFFERENT POLYNOMIAL DEGREES AT THREE MTR STATIONS

Polynomial Degrees	1	2	3	4
Station 1	3.16 m	3.09 m	2.81 m	3.22 m
Station 2	3.61 m	3.38 m	2.93 m	3.97 m
Station 3	3.31 m	3.18 m	2.62 m	3.56 m

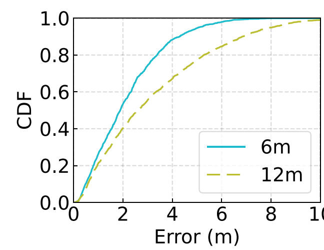

Fig. 24. BLE beacon density versus positioning accuracy.

logarithmic model [54], DeMo, DeMo utilizing only BLE signals (denoted as DeMo: BLE only), and an ideal localization scenario combining BLE signals with ground-truth velocity derived from passing two checkpoints (denoted as BLE+GTV). Using the traditional logarithmic model with BLE signals alone results in a mean positioning error of 3.22 m. In contrast, our new RSSI-distance model effectively reduces this error to 2.86 m. Further integrating IMU data analysis, DeMo significantly reduces the localization error to 2.17 m, demonstrating the effectiveness of utilizing IMU data for improving tracking accuracy. The 90th and 99th positioning errors are 4.29 m and 6.44 m, respectively. Meanwhile, we observe that in 2% of the test cases, DeMo experiences positioning errors exceeding 6 m. This large error is majorly due to failures in receiving the broadcast BLE beacon packets and does not affect DeMo's operation in practice. Not surprisingly, BLE+GTV achieves the best accuracy with a mean error of 1.70 m, while GTV is not feasible for practical deployment.

Furthermore, we evaluated positioning accuracy across 12 stations under diverse crowd densities at different times of the day. Recall that the training data was collected from one MTR station, and through a one-time parameter tuning process, we validated the RSSI-distance model across the remaining stations. To demonstrate our model's robustness, the overall mean localization errors, relying solely on BLE without IMU integration, are presented in Table X. The validation process was conducted through controlled experiments, as outlined in Section VII-A. To ensure a comprehensive evaluation, experiments were conducted under diverse crowd conditions, including peak hours when trains arrive, resulting in high pedestrian density, and late-night hours (e.g., after 11 PM) when pedestrian traffic is minimal. These scenarios captured a wide range of signal variations due to crowd obstruction, reflection, and movement dynamics.

In the majority of stations, positioning accuracy closely matched that of the initial station used for model training. However, two subway stations exhibited poorer positioning accuracy, specifically 3.68 m and 3.83 m. Unlike most subway stations, which typically feature long, narrow delivery areas, these two stations possess unique layouts with larger open spaces. This distinct layout can lead to reduced positioning accuracy within those open areas. Additionally, more severe beacon losses were observed in these two stations, inevitably affecting the positioning accuracy.

■ *Lesson 3: Without labor-intensive radio fingerprinting, an RSSI-distance model with customization is feasible to achieve accurate localization in complex environments. DeMo's integrated analysis of BLE and IMU readings yields an average positioning error of 2.17 m in dynamic and highly crowded MTR stations. This accuracy is adequate for common indoor applications [38], [55].*

RSSI-distance Models Comparison: Crowd obstruction and reflection severely degrade signal strength, potentially leading to signal loss, thus deviating from the traditional logarithmic model. To address this, we employ a polynomial function to model the impact of crowds on signal strength. Table XI presents the average positioning accuracy of 4 different polynomial models with degrees ranging from 1 to 4. Parameters of the RSSI-distance model were trained using data from one station and subsequently applied to other stations without retraining. We observed that models with higher polynomial degrees tended to overfit, while those with lower degrees exhibited unstable accuracy, influenced by subway crowds. Consequently, we selected a cubic polynomial function due to its superior accuracy compared to other polynomial degrees.

BLE Beacon Density: The beacon density affects the positioning accuracy. For the evaluation of beacon density in typical areas, we randomly selected one station with a beacon density of 6 m and adjusted the beacon density to 12 m by temporarily disabling some beacons. As shown in Fig. 24, the mean error increases from 2.17 m to 3.23 m. This is because a higher beacon density leads to more BLE packets received by DeMo and thus better positioning accuracy. A higher beacon density with an interval smaller than 6 m will further improve the localization accuracy, which is more than enough since the existing system

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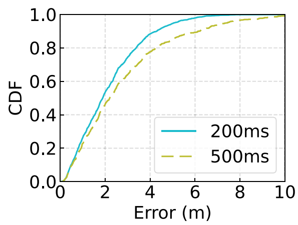

Fig. 25. Broadcast frequency versus positioning accuracy.

already satisfies the violation detection required by MTR stations. At the same time, a higher density significantly increases the deployment and maintenance costs, so it is not adopted in DeMo.

BLE Beacon Broadcast Frequency: Another factor affecting localization accuracy is beacon broadcast frequency. Fig. 25 compares the positioning error with beacon broadcast intervals of 200 ms and 500 ms at the same station, with all other parameters remaining constant. The mean localization error increases from 2.17 m to 2.78 m because DeMo's sensor receives more BLE packets with a smaller broadcast interval. Based on our four-year operational experience, the average battery life of a BLE beacon set to 200 ms is 22 months. This results in a maintenance cost of approximately 40 USD per station per month for replacing failed beacons.

■ *Lesson 4: DeMo aims at reliable monitoring under practical costs. It deploys sparse beacons for localization in most areas but adopts dense beacons for accurate store classification and reliable operation. Additional considerations such as maintenance cost and energy consumption also contribute to DeMo's trade-off.*

VIII. Related Work

Commercial Indoor Localization Systems: There are several BLE-based [24], [38], [50], [82] and WiFi-based [32] localization systems deployed in public indoor environments, such as airports, shopping malls, and museums, that provide clients with localization and navigation services. A prior study [38] leverages signal strength of BLE beacons and geomagnetic field strength as fingerprints to provide localization services in shopping malls, whereas DeMo employs a labor-free RSSI-distance model to achieve comparable localization accuracy. Recent studies [21], [22] have reported on the implementation of arrival detection systems within large-scale instant delivery operations, focusing on the real-time monitoring of couriers' indoor arrival status to optimize delivery efficiency. In contrast, DeMo offers fine-grained monitoring of delivery violations to enhance safety. Other real-world BLE systems have been deployed for presence detection [70], [71]. To our knowledge, there is very limited work on indoor delivery violation detection and regulation. Throughout the operation of DeMo, we have gained valuable insights that will inform future advancements in delivery safety.

Wireless Indoor Localization: Researchers have proposed a variety of wireless indoor localization techniques for navigation [4], [66], positioning [51], [68], [76], and asset tracking [43], [84]. Their design principles can be classified as RSSI propagation model [10], [15], [30], [37], [39], fingerprinting [5], [12], [25], [36], [55], [67], [72], Angle-of-Arrival model [3], [13], [44], [45], [79], and Time-of-Flight [4], [69]. While existing studies demonstrate good positioning accuracy, they are typically evaluated in small-scale environments. For example, Spotfi [45], ArrayTrack [79] and ToneTrack [80] achieve sub-meter localization accuracy by utilizing WiFi Channel State Information (CSI). Nevertheless, these systems are not applicable in real-world applications due to the lack of CSI support in most commercial WiFi access points and limited WiFi coverage in MTR stations. Similarly, Horus [85] also offers precise localization, but its deployment is challenging as it necessitates costly and recurring fingerprinting operations whenever environmental changes occur. In contrast, the in-the-wild operation of DeMo validates the feasibility of achieving accurate localization using simple RSSI models with low deployment and maintenance costs, while also providing several unique lessons and insights.

Deep Learning Based Sensing Solution: Recent years have witnessed significant advances in deep learning, which have inspired the adoption of deep learning-based approaches to address sensing challenges, including those in indoor localization [53] and sensing fusion [48]. The study [4] addresses both mapping and positioning simultaneously using a deep neural network with WiFi signals. Another study [33] employed RNNs to mitigate RSSI fluctuations, thereby enhancing localization accuracy. In DeMo, we utilize a learning-based approach to determine the destination store for each delivery.

IMU-Assisted Sensing System: These works [9], [83] analyze IMU's signal characteristics and extract the motion feature of humans to infer their posture, especially for Pedestrian Dead Reckoning [40]. This study [64] extracts step events from various types of periodic human behaviors by carrying a smartphone with IMU through CNN. Another study [2] improves positioning accuracy by inferring the posture direction of IMU readings. In addition to enhancing localization accuracy within complex environments, IMU can also contribute to recognizing fine-grained human activity, such as gesture recognition [87]. DeMo leverages IMU readings to detect special road surfaces and further improves speed accuracy, and provides reliable positioning service.

IX. Discussion

Limitations: (1) On-trolley sensor failure. The future design will incorporate more reliable hardware and additional protection methods to enhance device reliability. (2) Bypassing DeMo. Although DeMo covers 91% of deliveries, we intend to analyze delivery behaviors to identify potential bypass strategies and implement corresponding mitigations to achieve seamless monitoring coverage. (3) Delivery worker dissatisfaction. Despite DeMo's accurate violation detection, as evidenced by controlled experiments and positive feedback from MTR staff, our small-scale interviews indicate that delivery workers perceived DeMo as a surveillance system, leading to unfavorable reception.

Future Work: We intend to improve DeMo in the following ways: (1) Automatic parameter tuning. While our current RSSI-distance model achieves satisfactory accuracy through one-time parameter tuning based on data from a representative station, we observed degraded localization performance in a few stations with unique layouts or more severe beacon losses. To further

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enhance adaptability and scalability, a promising direction is automatic parameter tuning. Specifically, delivery trolleys typically remain stationary for 5–20 minutes during offloading at destination shops. During this time, DeMo can collect reliable BLE RSSI data. Once the delivery destination is confirmed by the store identification module, DeMo can use the BLE data to refine the RSSI-distance model via lightweight, on-device fine-tuning. This approach allows DeMo to dynamically adapt to environmental variations across stations, thereby improving positioning robustness without additional deployment overhead. (2) Generalizability to other indoor environments. Although DeMo is optimized for the MTR stations, its core architecture is applicable to other large indoor environments such as airports and hospitals. These spaces similarly feature structured layouts and service corridors, making them suitable for BLE/IMU-based tracking. We have conducted a small-scale deployment of DeMo in a hospital setting to track critical assets, requiring only minimal parameter reconfiguration. The system achieved meter-level localization accuracy in this new context, demonstrating its adaptability. So we plan to scale up this deployment and extend DeMo to other indoor environments (e.g., shopping malls). (3) Future hardware design and deployment. We aim to enhance hardware reliability under rough handling and redesign sensors to detect a wider range of violations. The MTR has identified that excessively high cargo can obstruct the delivery personnel's view, posing a risk to pedestrians. Consequently, cargo height detection has been mandated as a new violation category. We intend to improve our sensors and enhance the corresponding algorithm design, and expand DeMo's deployment to more stations.

X. Conclusion

Our experiences with DeMo demonstrate the feasibility of monitoring indoor delivery. Dedicated designs are essential to combat unique challenges and ensure reliable violation detection. DeMo outperforms the prior manual system by providing better coverage, effectively changing human behaviors, enhancing efficiency, and reducing costs. We hope these experiences and lessons will contribute to the development of future delivery monitoring systems, enhancing delivery safety.

References

[1] P. accident on escalator, "Here's why you really shouldn't wheel trolleys onto escalators," 2022. [Online]. Available: https://forums.hardwarezone.com.sg/threads/heres-why-you-really-shouldnt-wheel-strollers-trolleys-onto-escalators.6745840/

[2] M. Atashi, P. Malekzadeh, M. Salimibeni, Z. Hajiakhondi-Meybodi, K. N. Plataniotis, and A. Mohammadi, "Orientation-matched multiple modeling for RSSI-based indoor localization via BLE sensors," in *Proc. 28th Eur. Signal Process. Conf.*, 2021, pp. 1702–1706.

[3] R. Ayyalasomayajula et al., "LocAP: Autonomous millimeter accurate mapping of WiFi infrastructure," in *Proc. USENIX Symp. Netw. Syst. Des. Implementation*, 2020, pp. 1115–1129.

[4] R. Ayyalasomayajula et al., "Deep learning based wireless localization for indoor navigation," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2020, pp. 1–14.

[5] P. Bahl and V. N. Padmanabhan, "Radar: An in-building RF-based user location and tracking system," in *Proc. IEEE Conf. Comput. Commun.*, 2000, pp. 775–784.

[6] T. A. Bentley, "Slip, trip and fall accidents occurring during the delivery of mail," *Ergonomics*, vol. 41, no. 12, pp. 1859–1872, 1998.

[7] A. Bose and C. H. Foh, "A practical path loss model for indoor WiFi positioning enhancement," in *Proc. 6th Int. Conf. Inf., Commun. Signal Process.*, 2007, pp. 1–5.

[8] A. Brajdic and R. Harle, "Walk detection and step counting on unconstrained smartphones," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, 2013, pp. 225–234.

[9] V. Chandel, N. Ahmed, S. Arora, and A. Ghose, "InLoc: An end-to-end robust indoor localization and routing solution using mobile phones and BLE beacons," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2016, pp. 1–8.

[10] D. Chen, K. G. Shin, Y. Jiang, and K.-H. Kim, "Locating and tracking BLE beacons with smartphones," in *Proc. ACM Int. Conf. Emerg. Netw. EXperiments Technol.*, 2017, pp. 263–275.

[11] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining*, 2016, pp. 785–794.

[12] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, "FM-based indoor localization," in *Proc. ACM Int. Conf. Mobile Syst., Appl., Serv.*, 2012, pp. 169–182.

[13] Z. Chen et al., "AWL: Turning spatial aliasing from foe to friend for accurate WiFi localization," in *Proc. Int. Conf. Emerg. Netw. EXperiments Technol.*, 2017, pp. 238–250.

[14] L. Cheng, Z. Wang, Y. Zhang, W. Wang, W. Xu, and J. Wang, "Acouradar: Towards single source based acoustic localization," in *Proc. IEEE Conf. Comput. Commun.*, 2020, pp. 1848–1856.

[15] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proc. 16th Annu. Int. Conf. Mobile Comput. Netw.*, 2010, pp. 173–184.

[16] M. Corporation, "Welcome to LightGBM's documentation," 2024. [Online]. Available: https://lightgbm.readthedocs.io/en/stable/

[17] I. delivery accident, "Courier smashes passerby into paraplegia with escalator delivery," 2022. [Online]. Available: https://www.sohu.com/a/524951955_120823584

[18] DeMo, "IMU/BLE readings," 2023. [Online]. Available: https://github.com/Starry102/DeMo

[19] DeMo, "Parameters configuration," 2023. [Online]. Available: https://github.com/Starry102/DeMo/tree/main/train

[20] J. Diebel, "Representing attitude: Euler angles, unit quaternions, and rotation vectors," *Matrix*, vol. 58, no. 15/16, pp. 1–35, 2006.

[21] Y. Ding, L. Liu, Y. Yang, Y. Liu, D. Zhang, and T. He, "From conception to retirement: A lifetime story of a 3-year-old wireless beacon system in the wild," *IEEE/ACM Trans. Netw.*, vol. 30, no. 1, pp. 47–61, Feb. 2022.

[22] Y. Ding, Y. Yang, W. Jiang, Y. Liu, T. He, and D. Zhang, "Nationwide deployment and operation of a virtual arrival detection system in the wild," in *Proc. Conf. ACM Special Int. Group Data Commun.*, pp. 705–717, 2021.

[23] P. M. Djuric et al., "Particle filtering," *IEEE Signal Process. Mag.*, vol. 20, no. 5, pp. 19–38, Sep. 2003.

[24] F. T. Experience, "Gatwick's beacon installation provides augmented reality wayfinding," 2017. [Online]. Available: https://www.futuretravelexperience.com/on-the-ground/wayfinding-and-passenger-services/

[25] R. Faragher and R. Harle, "Location fingerprinting with Bluetooth low energy beacons," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2418–2428, Nov. 2015.

[26] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *IEEE Trans. Mobile Comput.*, vol. 11, no. 12, pp. 1983–1993, Dec. 2012.

[27] FindLaw, "Making a delivery via a service elevator," 1962. [Online]. Available: https://caselaw.findlaw.com/ca-court-of-appeal/1764404.html

[28] C. L. Firm, "Liquor delivery driver recovers $445,000 for fall on strip mall," 2020. [Online]. Available: https://www.clarklawnj.com/liquor-delivery-driver-recovers-445000-for-fall-on-strip-mall-macadam

[29] Y. Gao et al., "XINS: The anatomy of an indoor positioning and navigation architecture," in *Proc. 1st Int. Workshop Mobile Location-Based Serv.*, 2011, pp. 41–50.

[30] Y. Gu and F. Ren, "Energy-efficient indoor localization of smart handheld devices using Bluetooth," *IEEE Access*, vol. 3, pp. 1450–1461, 2015.

[31] B. Guo et al., "WePos: Weak-supervised indoor positioning with unlabeled WiFi for on-demand delivery," *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 6, no. 2, pp. 54:1–54:25, Jul. 2022.

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[32] D. Han, S. Jung, M. Lee, and G. Yoon, "Building a practical Wi-Fi-based indoor navigation system," *IEEE Pervasive Comput.*, vol. 13, no. 2, pp. 72–79, Second Quarter 2014.

[33] M. T. Hoang, B. Yuen, X. Dong, T. Lu, R. Westendorp, and K. Reddy, "Recurrent neural networks for accurate RSSI indoor localization," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10639–10651, Dec. 2019.

[34] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[35] Z. Hong et al., "CrossHAR: Generalizing cross-dataset human activity recognition via hierarchical self-supervised pretraining," *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 8, no. 2, May 2024, Art. no. 64.

[36] A. M. Hossain and W.-S. Soh, "Cramer-rao bound analysis of localization using signal strength difference as location fingerprint," in *Proc. IEEE Conf. Comput. Commun.*, 2010, pp. 1–9.

[37] A. M. Hossain and W.-S. Soh, "A survey of calibration-free indoor positioning systems," *Comput. Commun.*, vol. 66, pp. 1–13, 2015.

[38] Y. Hu et al., "Experience: Practical indoor localization for malls," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2022, pp. 82–93.

[39] Y. Ji, S. Biaz, S. Pandey, and P. Agrawal, "ARIADNE: A dynamic indoor signal map construction and localization system," in *Proc. ACM Int. Conf. Mobile Syst., Appl., Serv.*, 2006, pp. 151–164.

[40] A. R. Jimenez, F. Seco, C. Prieto, and J. Guevara, "A comparison of pedestrian dead-reckoning algorithms using a low-cost MEMS IMU," in *Proc. IEEE Int. Symp. Intell. Signal Process.*, 2009, pp. 37–42.

[41] C. Joints, "Guidance notes on panelling design and joint construction of concrete slabs," 2021. [Online]. Available: https://www.hyd.gov.hk/en/technical_references/technical_document/guidance_notes/pdf/gn020a.pdf

[42] W. Kang and Y. Han, "SmartPDR: Smartphone-based pedestrian dead reckoning for indoor localization," *IEEE Sensors J.*, vol. 15, no. 5, pp. 2906–2916, May 2015.

[43] C.-H. Kao, R.-S. Hsiao, T.-X. Chen, P.-S. Chen, and M.-J. Pan, "A hybrid indoor positioning for asset tracking using bluetooth low energy and Wi-Fi," in *Proc. IEEE Int. Conf. Consum. Electron. - Taiwan*, 2017, pp. 63–64.

[44] A. Kludze, R. Shrestha, C. Miftah, E. Knightly, D. Mittleman, and Y. Ghasempour, "Quasi-optical 3D localization using asymmetric signatures above 100 GHz," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2022, pp. 120–132.

[45] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, "SpotFi: Decimeter level localization using WiFi," in *Proc. ACM SIGCOMM*, 2015, pp. 269–282.

[46] C. Li, M. Mirosa, and P. Bremer, "Review of online food delivery platforms and their impacts on sustainability," *Sustainability*, vol. 12, no. 14, 2020, Art. no. 5528.

[47] M. Li, N. Liu, Q. Niu, C. Liu, S.-H. G. Chan, and C. Gao, "Sweeploc: Automatic video-based indoor localization by camera sweeping," *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 2, no. 3, pp. 1–25, 2018.

[48] S. Liu et al., "GiobalFusion: A global attentional deep learning framework for multisensor information fusion," *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 4, no. 1, pp. 1–27, 2020.

[49] M. Liwicki, A. Graves, S. Fernàndez, H. Bunke, and J. Schmidhuber, "A novel approach to on-line handwriting recognition based on bidirectional long short-term memory networks," in *Proc. Int. Conf. Document Anal. Recognit.*, 2007, pp. 367–371.

[50] Locatify, "Intuitively designed beacon based museum audio guide," 2020. [Online]. Available: https://locatify.com/blog/eldheimar-museum/

[51] C. Luo, H. Hong, M. C. Chan, J. Li, X. Zhang, and Z. Ming, "MPiLoc: Self-calibrating multi-floor indoor localization exploiting participatory sensing," *IEEE Trans. Mobile Comput.*, vol. 17, no. 1, pp. 141–154, Jan. 2018.

[52] A. Mackey, P. Spachos, L. Song, and K. N. Plataniotis, "Improving BLE beacon proximity estimation accuracy through Bayesian filtering," *IEEE Internet Things J.*, vol. 7, no. 4, pp. 3160–3169, Apr. 2020.

[53] A. Nessa, B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE Access*, vol. 8, pp. 214945–214965, 2020.

[54] H. A. Nguyen, H. Guo, and K.-S. Low, "Real-time estimation of sensor node's position using particle swarm optimization with log-barrier constraint," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 11, pp. 3619–3628, Nov. 2011.

[55] J. Ni et al., "Experience: Pushing indoor localization from laboratory to the wild," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2022, pp. 147–157.

[56] "T. G. of the Hong Kong special administrative region. wages and labour earnings," 2022. [Online]. Available: https://www.censtatd.gov.hk/tc/scode210.html

[57] A. on escalator, Transport goods by escalator, 2022. [Online]. Available: https://orientaldaily.on.cc/cnt/news/20160223/00176_125.html

[58] A. Opher, A. Chou, A. Onda, and K. Sounderrajan, *The Rise of the Data Economy: Driving Value Through Internet of Things Data Monetization*. Armonk, NY, USA: IBM Corp., 2016.

[59] G. Palshikar et al., "Simple algorithms for peak detection in time-series," in *Proc. Int. Conf. Adv. Data Anal. Bus. Anal. Intell.*, 2009, pp. 1–12.

[60] T. Paving, "Design manual:barrier free access," 2021. [Online]. Available: https://www.bd.gov.hk/doc/en/resources/codes-and-references/code-and-design-manuals/BFA2008_e.pdf

[61] J. Racko, P. Brida, A. Perttula, J. Parviainen, and J. Collin, "Pedestrian dead reckoning with particle filter for handheld smartphone," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2016, pp. 1–7.

[62] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-effort crowdsourcing for indoor localization," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2012, pp. 293–304.

[63] S. Rodriguez Garzon and B. Deva, "Geofencing 2.0: Taking location-based notifications to the next level," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, 2014, pp. 921–932.

[64] W. Shao, H. Luo, F. Zhao, C. Wang, A. Crivello, and M. Z. Tunio, "DePedo: Anti periodic negative-step movement pedometer with deep convolutional neural networks," in *Proc. IEEE Int. Conf. Commun.*, 2018, pp. 1–6.

[65] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang, "Walkie-markie: Indoor pathway mapping made easy," in *Proc. USENIX Symp. Netw. Syst. Des. Implementation*, 2013, pp. 85–98.

[66] S. Shen, N. Michael, and V. Kumar, "Autonomous multi-floor indoor navigation with a computationally constrained MAV," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2011, pp. 20–25.

[67] Y. Shu, K. G. Shin, T. He, and J. Chen, "Last-mile navigation using smartphones," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2015, pp. 512–524.

[68] M. L. Sichitiu and V. Ramadurai, "Localization of wireless sensor networks with a mobile beacon," in *IEEE Int. Conf. Mobile Ad-Hoc Sensor Syst*, 2004, pp. 174–183.

[69] E. Soltanaghaei, A. Kalyanaraman, and K. Whitehouse, "Multipath triangulation: Decimeter-level WiFi localization and orientation with a single unaided receiver," in *Proc. Int. Conf. Mobile Syst., Appl., Serv.*, 2018, pp. 376–388.

[70] F. Technologies, "Eddystone beacon installation at indian railway stations," 2018. [Online]. Available: https://www.fabliantechnologies.com/eddystone-beacon-installation-at-indian-railway-stations-by-google/

[71] Thinkproxi, "Thinkproxi announces famous beale street implemented beacon technology," 2017. [Online]. Available: https://www.thinkproxi.com/thinkproxi-announces-famous-beale-street-implemented-beacon-technology/

[72] X. Tian, R. Shen, D. Liu, Y. Wen, and X. Wang, "Performance analysis of RSS fingerprinting based indoor localization," *IEEE Trans. Mobile Comput.*, vol. 16, no. 10, pp. 2847–2861, Oct. 2017.

[73] A. Vaswani et al., "Attention is all you need," in *Proc. Int. Conf. Neural Inf. Process. Syst.*, 2017, pp. 6000–6010.

[74] X. Wang, L. Gao, S. Mao, and S. Pandey, "CSI-based fingerprinting for indoor localization: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 763–776, Jan. 2017.

[75] M. Werner, M. Kessel, and C. Marouane, "Indoor positioning using smartphone camera," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2011, pp. 1–6.

[76] C. Wu, Z. Yang, Y. Liu, and W. Xi, "WILL: Wireless indoor localization without site survey," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 4, pp. 839–848, Apr. 2013.

[77] H. Wu, S. He, and S.-H. G. Chan, "Efficient sequence matching and path construction for geomagnetic indoor localization," in *Proc. Int. Conf. Embedded Wireless Syst. Netw.*, 2017, pp. 156–167.

[78] Y. Wu et al., "Google's neural machine translation system: Bridging the gap between human and machine translation," 2016, *arXiv: 1609.08144*.

[79] J. Xiong and K. Jamieson, "ArrayTrack: A fine-grained indoor location system," in *Proc. USENIX Symp. Netw. Syst. Des. Implementation*, 2013, pp. 71–84.

[80] J. Xiong, K. Sundaresan, and K. Jamieson, "Tonetrack: Leveraging frequency-agile radios for time-based indoor wireless localization," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2015, pp. 537–549.

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[81] J. Yang et al., "Detecting driver phone use leveraging car speakers," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2011, pp. 97–108.
[82] Y. Yang et al., "Transloc: Transparent indoor localization with uncertain human participation for instant delivery," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2020, pp. 1–14.
[83] P. K. Yoon, S. Zihajehzadeh, B.-S. Kang, and E. J. Park, "Adaptive Kalman filter for indoor localization using Bluetooth low energy and inertial measurement unit," in *Proc. IEEE 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2015, pp. 825–828.
[84] J.-H. Youn, H. Ali, H. Sharif, J. Deogun, J. Uher, and S. H. Hinrichs, "WLAN-based real-time asset tracking system in healthcare environments," in *Proc. IEEE Int. Conf. Wireless Mobile Comput., Netw. Commun.*, 2007, pp. 71–71.
[85] M. Youssef and A. Agrawala, "The horus WLAN location determination system," in *Proc. ACM Int. Conf. Mobile Syst., Appl., Serv.*, 2005, pp. 205–218.
[86] Y. Yu, D. Wang, R. Zhao, and Q. Zhang, "RFID based real-time recognition of ongoing gesture with adversarial learning," in *Proc. 17th Conf. Embedded Netw. Sensor Syst.*, 2019, pp. 298–310.
[87] D. Zhang et al., "Fine-grained and real-time gesture recognition by using IMU sensors," *IEEE Trans. Mobile Comput.*, vol. 22, no. 4, pp. 2177–2189, Apr. 2023.

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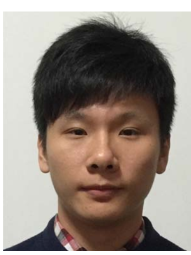

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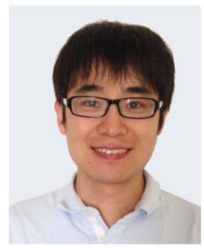

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