Passengers' Safety Matters: Experiences of Deploying a Large-Scale Indoor Delivery Monitoring System

Xiubin Fan[1], Zhongming Lin[2], Yuming Hu[3], Tianrui Jiang[2], Feng Qian[4],

Zhimeng Yin[1,*], S.-H. Gary Chan[2,*], Dapeng Wu[1]

[1]*City University of Hong Kong* [2]*The Hong Kong University of Science and Technology* [3]*University of Minnesota – Twin Cities*
[4]*University of Southern California*

Abstract

Delivering goods to many indoor stores poses significant safety issues, as heavy, high-stacked packages carried on delivery trolleys may fall and hurt passersby. This paper reports our experiences of developing and operating DeMo, a practical system for real-time monitoring of indoor delivery. DeMo attaches sensors to trolleys and analyzes the Inertial Measurement Unit (IMU) and Bluetooth Low Energy (BLE) readings to detect delivery violations such as speeding and using non-designated delivery paths. Differing from typical indoor localization applications, DeMo overcomes unique challenges such as unique sensor placement and complex electromagnetic characteristics underground. In particular, DeMo adapts the classical logarithmic radio signal model to support fingerprint-free localization, drastically lowering the deployment and maintenance cost. DeMo has been operating since May 2020, covering more than 200 shops with 42,248 deliveries (3521.4 km) across 12 subway stations in Hong Kong. DeMo's 3-year operation witnessed a significant violation rate drop, from 19% (May 2020) to 2.7% (Mar 2023).

1 Introduction

Indoor localization has been extensively studied by the research community [4, 5, 19, 39, 41, 43, 64, 66]. Very recently, there emerged commercial, large-scale indoor localization systems that leverage the two-decade research to benefit end customers (*e.g.,* mall navigation [30, 43] and presence detection [18, 19]) and even offer monetization opportunities [46].

In this paper, we investigate a unique and important application that falls into the broad topic of indoor localization: *indoor delivery monitoring*. Many public places such as airports, subway stations, malls, and office buildings feature dense retail stores and crowded visitors. Delivering goods to the stores (Fig. 1) poses significant safety issues, as heavy, high-stacked packages carried on delivery trolleys may fall and hurt passersby. The particular indoor environments may exacerbate such a risk: there are usually no corridors reserved exclusively for delivery; the uneven road surfaces such as slopes, tactile pavings, and contraction joints make packages less stable; delivery personnel may even use passenger lifts, whose acceleration and deceleration may make packages fall. Reckless indoor delivery has resulted in severe injury or even deaths [1, 14, 21, 45, 57, 62]. 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 [45]. When indoor environments are crowded, delivery accidents may be more severe compared to their outdoor counterparts [6, 38], and they may trigger cascading accidents such as crowd collapse and even stampedes where the death toll can reach hundreds.

Fig. 1: Indoor delivery in an MTR station.

As an advocator of indoor delivery safety, Hong Kong Electrical and Mechanical Services Department (HK EMSD) has been strictly monitoring delivery violations in Mass Transit Railway (MTR) stations in HK. MTR has a daily ridership of more than 5 million (Feb 2023). Henceforth, its stations are dense with passengers, stores, and indoor deliveries. EMSD has established four 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) performing delivery in peak hours. To ensure the rules are being properly followed, since 2010, MTR has been hiring safety staff to manually monitor the delivery behavior. The staff needs to physically follow the delivery worker and manually document observed violations. Clearly, this approach is inaccurate (in particular for speed estimation), unscalable, and labor-intense.

To address the disadvantages of the manual efforts, we collaborated with HK EMSD and MTR on devising a fully automated indoor delivery monitoring solution, referred to as DeMo. In this paper, we report our multi-year experiences of developing, deploying, and maintaining DeMo. Our system was commercially deployed in 12 MTR stations for monitoring 40K+ deliveries to 200+ stores since May 2020.

At a first glance, it appears that we can trivially apply an existing indoor localization solution (Table 1) 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 face several unique challenges and practical constraints that

*Zhimeng Yin and S.-H. Gary Chan are co-corresponding authors.

Table 1: Large-scale indoor operational systems. "B+G" means BLE and geomagnetic fields; "det." represents detection; "prop." is for propagation; "mon." means monitoring.

System	Technique	Signal	Application
MLoc [30]	Fingerprinting	B+G, IMU	Navigation
Tencent [43]	Fingerprinting	WiFi, IMU	Navigation
myCoex [27]	Fingerprinting	WiFi	Navigation
aBeacon [18]	Proximity det.	BLE	Presence det.
VALID [19]	Proximity det.	BLE	Presence det.
DeMo	Prop. model	BLE, IMU	Delivery mon.

render off-the-shelf indoor localization solutions not applicable. First, *the sensor placement is different*. Unlike prior 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 [34, 53]. Again due to the sensor placement, sensor readings are significantly disturbed when the trolley moves over special ground surfaces such as tactile pavings and contraction joints. 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 demonstrated in Appendix A.1. Consequently, we cannot adopt commonly used features, *e.g.,* geomagnetic field (GMF) strength. Due to the same reason, we are not even able to obtain the accurate moving direction that is essential for position tracking. Third, due to *privacy concern and loud noises* in MTR stations, we cannot use vision-based or acoustic-based localization; due to *constraints of device form factor and energy usage*, we are not allowed to adopt WiFi-based localization either, which was heavily researched [13, 50, 65] and commercially deployed [27, 43]. 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 [27, 30], because training and maintaining the fingerprint database requires significant labor in crowded MTR stations.

To tackle the above challenges, DeMo only uses cheap, lightweight Bluetooth Low Energy (BLE) beacons as the infrastructure. To further lower the deployment bar, instead of using BLE beacons' RSSI readings as location fingerprints, we adopt a simple RSSI-distance model as the core localization mechanism. The model is generic across all MTR stations; it thus eliminates the need for training and updating the per-site fingerprint database. While RSSI propagation modeling has been extensively studied [5, 7, 13, 31, 42], our contribution lies in *adapting the classical logarithmic model [42] to complex indoor environments, and for the first time, demonstrate its efficacy in supporting fingerprint-free localization through large-scale commercial deployment*. Specifically, we note that in MTR stations where occlusion, interference, and dynamic crowds are common, abrupt RSSI change and weak RSSI values can cause significant ranging errors and fluctuations. Therefore, we adjust the classical free-space propagation model to accommodate these unique challenges in complex MTR environments. Meanwhile, we properly calibrate our model through one-time training and then adopt it across MTR stations. Experiments indicate that our adjusted model significantly outperforms the literature [5, 7, 13, 31, 42], many requiring sophisticated tuning such as ray tracing.

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. 7). 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.

Last but not least, we integrate the above components (RSSI model, speed measurement, surface detection, PF-based localization), together with other essential modules (floor plan processing, violation detection/alarming, store classification, 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 3-year deployment (42K+ deliveries to 200+ shops, with 3521.4 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 3-year operation witnessed a significant violation rate drop, from 19% (May 2020) to 2.7% (Mar 2023). 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.
- Compared to manual delivery monitoring used before 2020, DeMo improved the monitoring coverage (*i.e.,* the fraction of detected delivery events) from 53% to 88%, and meanwhile reduced the operational cost by 8X.
- 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 [69]). 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 contribution consists of the following. (1) We develop DeMo, a first commercially deployed indoor delivery monitoring system. (2) Through the 3-year deployment of DeMo, we learn several key lessons and operational experiences. (3) Most importantly, DeMo indeed makes HK MTR safer, benefiting millions of riders every day. Note that DeMo can be potentially extended to broader indoor services such as property management [73] for monitoring shuttle vehicles in shopping malls and 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 facilitate further research, we have released our collected IMU and BLE readings on GitHub [15].

2 Motivation

Delivery Violations. The MTR is a major public transportation network that transports around 5 million daily passengers in HK. To facilitate commuter needs, MTR stations offer diverse shops (including food/beverage, health/beauty, books, banking, and convenience stores), similar to typical small malls in many countries. Because of the crowded MTR stations, indoor delivery has a potential risk and EMSD in HK requires strict monitoring of delivery behaviors in MTR stations. Targeting the specific scenario of delivery in 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 safe deliveries following government guidelines, MTR stations hire additional safety staff for manual monitoring. These safety staff need to follow each delivery, warn delivery workers once they observe a violation, and file delivery reports for future action. These delivery reports include the delivery time, path, and violation type (if there exists a violation) [2].

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

[2] One delivery record example: station code KXX, entry/exit A, start time 5/10/21 10:05, shop ID K001, violation type 2.

Not surprisingly, the current manual system has substantial limitations. (1) It is difficult to visually monitor delivery workers' moving speed, which leads to potential violations and safety risks. (2) Manual recording requires substantial human resources - a safety staff is required for each delivery. It is impossible for one safety staff to monitor multiple deliveries concurrently, leading to monitoring failures. (3) High labor cost. Each station requires multiple safety staff depending on its scale, which directly adds up to a high expense.

The above limitations motivate us to design a fully automated system with reliable monitoring services and reduced costs - DeMo. During DeMo's design and prototyping, we discovered a few unique challenges, such as IMU readings' large fluctuation due to special road surfaces and the severe electromagnetic environment, which need to be addressed in practice for reliable monitoring.

3 System Design

3.1 An Overview of System

DeMo consists of two phases: *offline preparatory phase* and *online operational phase*.

Offline Preparatory Phase. In this phase, we design customized sensors that will be attached to trolleys for delivery monitoring. Then we strategically deploy BLE beacons in MTR stations to balance the monitoring reliability and deployment/maintenance cost. To completely remove the intensive radio fingerprinting cost in many wireless localization systems, we adopt a Received Signal Strength Indication (RSSI) to distance model that is quickly applied across different scenarios with reliable accuracy. In addition, we further process the MTR station floor maps. The preparatory phase's details are discussed in Sec. 3.2.

Online Operational Phase. Fig. 2 shows the operational DeMo. When reaching an MTR station entrance, delivery workers receive DeMo's sensors from MTR staff and then attach sensors to workers' own trolleys that satisfy different shops' specific supply requirements.

During delivery, workers manually drive trolleys that carry supply goods while DeMo monitors the whole procedure. Specifically, DeMo calculates the moving speed (Sec. 3.3) using IMU readings. For the trolley trajectory generation (Sec. 3.4), DeMo adopts a particle filter to leverage received BLE packets and estimated speed. Although the idea seems straightforward, DeMo needs to address a few unique challenges in MTR stations, *e.g.,* 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 analyzes them for violation detection (Sec. 3.5).

When arriving at the target store, delivery workers unload their goods which usually lasts 5-20 minutes. DeMo utilizes this opportunity to identify the specific store and alleviates the possible false alarms by analyzing the historical IMU+BLE readings. Then, DeMo uploads the delivery record to the

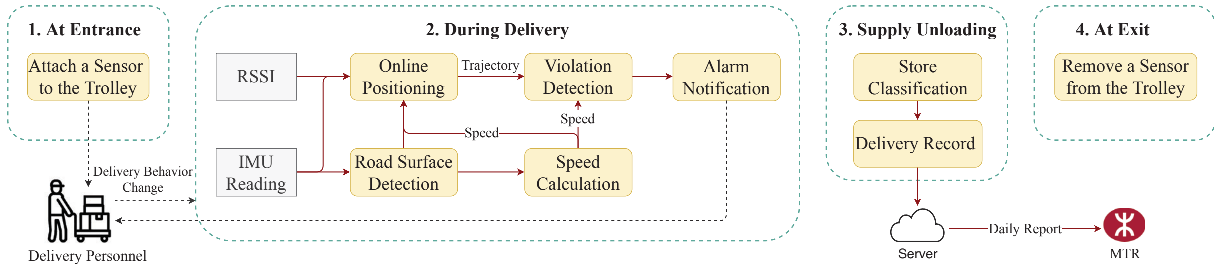

Fig. 2: DeMo system overview (operational phase).

server which analyzes the daily violation rate to identify abnormally high violations. When delivery workers reach an MTR exit, they return DeMo's sensors to MTR staff.

3.2 Offline Preparatory Phase

Our offline phase includes signal choice, sensor design, floor plan processing, BLE beacon deployment, and RSSI-distance model verification.

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:

• The privacy issue restricts us from installing privacy-intrusive devices, such as cameras or depth cameras.

• As required by MTR stations, we are only allowed to install small-sized battery-powered devices and cannot place power cables. As a result, it is infeasible to install power-hungry devices such as WiFi access points, while MTR stations have limited WiFi coverage and require dedicated WiFi access points for WiFi-based localization.

• Acoustic and light-based indoor localization systems are not practical due to challenges such as noise, reverberation, limited visibility, and complexity.

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

Sensor Design. In addition to commodity BLE beacons deployed in MTR stations, we customize on-trolley sensors with two major components, Raspberry PI 4B and customized hardware attached on top (HAT) in Fig. 4. 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.

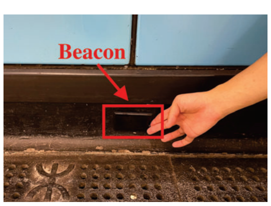

Fig. 3: Sender: a beacon deployed on the skirting board.

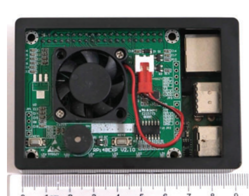

Fig. 4: Receiver: Raspberry PI 4B and customized HAT.

Our sensor captures BLE packets via a Bluetooth chipset and detects violations in real-time. Once detecting a violation, it alarms through a speaker and also reports to the server through a 4G dongle. Since this report contains only essential information (*e.g.,* sensor id, station, entry/exit, delivery time, destination shop, and violation type), it requires moderate energy consumption. The overall energy consumption for DeMo's sensing, computation, and uploading is around 400 mW. We chose the Raspberry PI to reduce our hardware design workload, while its operating system accounts for the majority of the energy consumption (2000 mW). Our sensor is connected to a small-capacity portable power bank that is charged roughly every 2 days.

BLE Beacon Deployment. MTR stations impose strict aesthetic constraints on BLE beacon deployment. We adopt small-size, battery-powered, and black-coated beacons and deploy them at skirting board locations (Fig. 3) near the ground. The beacon distance is 6 to 8 meters in the majority of areas. During DeMo's initial trial, we noticed several areas that often lead to large errors or are critical in DeMo's operation. This inspires us to adopt dedicated deployment strategies for these areas. For large pillars, we deploy beacons on all four sides to alleviate signal obstruction. For in-station stores, we deploy 3 beacons (two outside and one inside the store) to improve the store classification accuracy.

During DeMo's operation, we also recognize the beacon types affect our maintenance. Table 2 shows two types of beacons primarily used for DeMo. In our initial few stations, we deployed beacon type 1 but noticed a significant loss rate, reaching 9% after 5 months (Sec. 4.4). This loss is caused by the high chances of collisions with passengers. To alleviate maintenance costs, we turned to beacon type 2, which is more expensive with a card shape. This card shape offers larger contact areas for gluing and reduces the chances of colliding with walking passengers with better reliability, around 2.3% after 5 months. This motivates us to only deploy beacon type 2 in later deployment/maintenance. Overall, we have deployed DeMo in 12 MTR stations with more than 1,500 beacons.

RSSI-Distance Model Verification. Many localization systems [11, 23, 24, 30, 63] 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, 13, 31, 42], its verification is fundamentally missing in large-scale settings. In contrast, DeMo adopts a low-cost and accurate RSSI-

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

Table 2: Beacon type comparison.

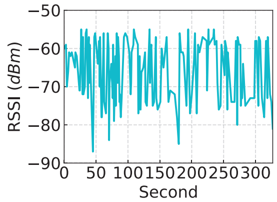

Fig. 5: Abrupt RSSI change with time at a static sensor.

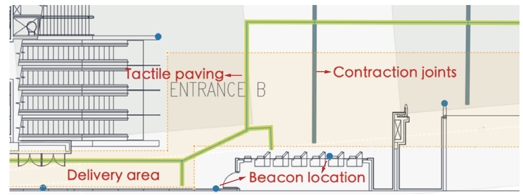

Fig. 6: Pre-processed floor plan. Yellow regions represent designated delivery areas.

distance model for large-scale operation.

We started with classic free-space propagation models, *e.g.,* the well-known logarithmic model $r = r_0 + 10N \log d + X_\sigma$ [42]. 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. 5 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, 13]) 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 R_{th} (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 the Appendix A.2. 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 [16]. To mitigate the highly dynamic crowds, DeMo adopts a sliding window t_{sw} 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. There is no significant accuracy difference between these areas. The overall mean localization error solely based on BLE without IMU (Sec. 5.3) is 2.81 m. Then, we further validate our model across the remaining stations without parameter retraining. Detailed results are included in Appendix A.3. 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 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 [16].

■ **Finding 1** *Without labor-intensive site surveys, a good RSSI model with necessary customization 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 [51] 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. We also examine MTR stations' ground surface conditions. 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

Sec. 3.3). Note that DeMo avoids tedious examination of each station since MTR stations' surfaces follow specific construction regulations and exhibit very similar IMU patterns. Fig. 6 shows an example of the pre-processed floor plan.

3.3 Online Speed Detection

DeMo estimates the trolley's real-time speed by analyzing IMU readings with two major 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 [48] and contraction joints [33]) lead to large IMU fluctuations and speed estimation errors when a trolley passes these surfaces. Specifically, tactile pavings (Fig. 7(a)) consist of 4 parallel bars and are widely used to assist pedestrians with vision impairment. Contraction joints (Fig. 7(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.

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

Fig. 7: Examples of tactile paving, contraction joints, and a normal road.

Fig. 8 compares the IMU readings when a trolley passes different surfaces. These large IMU fluctuations inspire us to adopt peak detection [47] 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 $t_1 \dots t_n$, 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 current surface is recognized as tactile paving. DeMo adopts a similar strategy to detect a contraction joint, if n is 2 and each of $t_1 \dots t_n$ is between 0.2 and 1 second. 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. DeMo analyzes IMU readings for accurate speed estimation with the following procedures.

• *Sensor status detection.* When the a_{std} is under 0.01 g [50], 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 [25, 34, 50] methods could be adopted to recognize human walking patterns like step detection for speed inference, as widely discussed in literature [30, 49, 55]. 2) Our sensor is placed on a trolley. DeMo recognizes this placement if IMU readings lack human walking patterns [8]. Based on DeMo's operational results (Sec. 4.3), our sensor is placed on trolleys for 95% of deliveries.

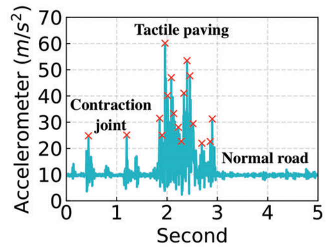

Fig. 8: IMU readings at different surfaces.

• *Adaptive integral of IMU readings.* For a on-trolley sensor[3], 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.*

3.4 Online Positioning

DeMo leverages a particle filter (PF) [20] to recursively update the probability distribution for tracking the trolley position in real-time. We choose PF DeMo 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 that have the same weight and are evenly distributed over 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 reading to calculate the Euler angle [17] and move each particle to a new position based on the variance of the yaw angle and the speed produced from Sec. 3.3. In practice, we observe a high variance of the yaw angle when

[3]For in-hand or in-pocket sensor, DeMo leverages existing techniques for speed estimation [34].

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 (Sec. 3.2). 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%.

3.5 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 Sec. 3.3 with the regulation (1.5 m/s) to detect if there is a speed violation. Then DeMo leverages the positioning results calculated in Sec. 3.4 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 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.

4 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 42,248 deliveries with a 3521.4 km delivery length. By default, the beacons have a broadcast interval of 200 ms, and the sample rate of IMU is 500 Hz.

4.1 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 0.5% in 2023. Fig. 9 shows DeMo's detection results of speeding violations[4]. 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 Sec. 5.2) 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 2.7% in March 2023.

Prior to DeMo, MTR stations also adopted a manual monitoring system for many years without such an achievement. Given that DeMo effectively monitors more than 88% of the total delivery events [5], 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 Sec. 3.1 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 3 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.

Table 3: A/B testing.

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

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

[5]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. 88% 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.

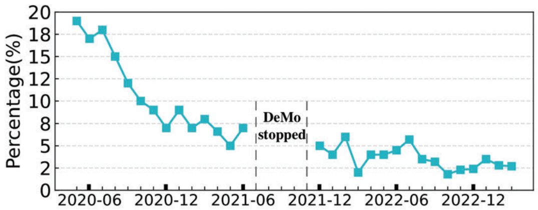

Fig. 9: Violation (speeding) rate.

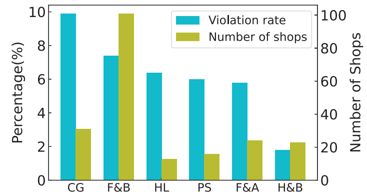

Fig. 10: Distribution of violation shops.

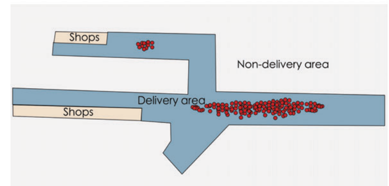

Fig. 11: A field study of the speeding area.

■ **Lesson 1** *DeMo's 3-year large-scale operation effectively reduces the violation rate from 19% to 2.7%. 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. 10. 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.

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 MTR stations take specific countermeasures to improve safety. Fig. 11 shows one example of the clustered violation distribution, where each dot represents a speeding violation.

4.2 DeMo vs. Manual Monitoring

Compared with manual monitoring/recording via hired MTR staff[6], 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 2.7% as demonstrated in Sec. 4.1, 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 42,248 deliveries, covering 88% of the total delivery activities on average (verified with the total number of delivery activities), much better than the 53% monitoring rate offered in manual monitoring. The missing cases are largely the result of insufficient sensors at some subway stations and sensor hardware failures due to 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)[7]. 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-20K 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 [44]. After DeMo's 3-year operation, the cost of manual monitoring is at least 8X 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 2.7%), monitoring efficiency (DeMo detects 88% of the total delivery events in contrast to the prior 53%), and cost reduction ($> 8X$).*

4.3 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 reading 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. 12 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

[6] 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.

[7] The prices were in 2020.

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 Sec. 5.3.

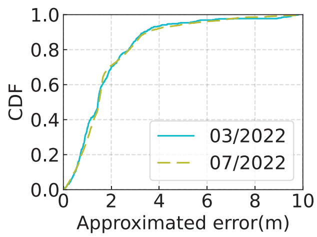

Fig. 12: Approximated positioning error in 2022.

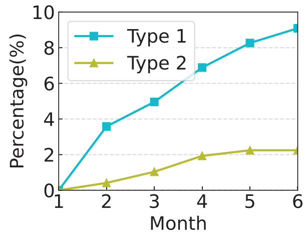

Fig. 13: Beacon failure rate with time in 2020.

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.

4.4 System Maintenance

This section analyzes DeMo's maintenance cost.

Impact of Beacon Types. Our initial deployment adopted beacon type 1 but noticed a high loss rate caused by various reasons, such as natural falls and collisions with passengers. This high loss rate motivated us to switch to beacon type 2 in our latter deployment or maintenance, as discussed in Sec. 3.2. Fig. 13 shows the beacon failure rate with time. After 5 months, the loss rate of type 1 reached 9%, while type 2 was only around 2.3%. This experiment validates that appropriate beacon selection could effectively reduce maintenance costs.

Failed Beacon Location. Table 4 offers 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 have the highest beacon loss rates, which is likely to be caused by the dense crowd. For locations with high loss rates, we increase the beacon broadcast frequency (*e.g.,* 100 ms) to compensate for lost beacons and leverage the deployed beacons before they fail.

Table 4: Beacon failure with the location.

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

■ **Finding 4** *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.*

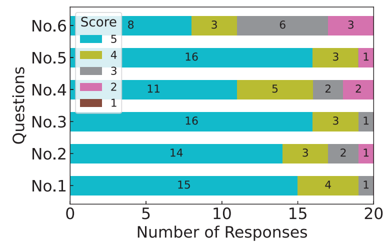

Fig. 14: Feedback from 20 MTR staff.

4.5 MTR Feedback

We designed a questionnaire to evaluate DeMo's performance and Fig. 14 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. satisfaction with our system, 2. low complexity of device usage, 3. effect on violation reduction, 4. speed detection accuracy, 5. decrease of workload, and 6. frequency of sensor damage. The detailed questionnaire is included in the Appendix A.5. We summarize these questions with 4 takeaway messages.

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 (agree) or 5 (strongly agree). The major takeaway messages are as follows.

(1) User friendly. The operation of DeMo is easy and convenient without complicated knowledge.

(2) Violation rate decrease. DeMo effectively decreases the violation rate by correcting delivery behaviors.

(3) Workload reduction. DeMo effectively reduces 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 5** *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.*

5 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 Sec. 4. Our controlled experiments last 15 days and cover 0.9k delivery cases with a total length of approximately 54 km.

5.1 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.

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.

5.2 Violation Detection Reliability

We evaluate DeMo's detection reliability for four violations mentioned in Sec. 2. 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 a total number of 86 violations. Each delivery only 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 5 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 5 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 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 5, demonstrating its reliability in practice.

Table 5: 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

■ **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.*

5.3 System Performance

Speed Detection Accuracy. We compare three speed calculation methods: the algorithm used in DeMo, traditional integral without road surface detection, and positioning-based approach (the speed is calculated from the localization results). The ground truth speed is calculated from the hired delivery personnel's ground-truth locations and the time passing them.

Fig. 15 shows the overall speed detection error. Not surprisingly, the position-based approach leads to the highest mean speed error of 0.52 m/s. This is because the localization includes 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 the IMU errors. For the speed detection based on direct integral, the mean error is 0.43 m/s. For DeMo, it detects the special road surfaces and further excludes them to improve its speed detection accuracy, leading to a mean error of 0.31 m/s. The tail improvement is much more significant: the third quartile error decreases from 0.62 m/s to 0.44 m/s, meaning that the speeding violation detection is much more reliable.

Impact of Delivery Path Length. Table 6 shows the distribution of the delivery length from the station entry to the destination shop. Fig. 16 demonstrates trolley speed estimation errors under the different path lengths of 50m, 100m, 200m. In general, we observe a smaller error (median error of 0.18 m/s) for short paths (<50 m), while long paths (100-200 m) exhibit larger errors (median error of 0.23 m/s). This difference is because the integral error accumulates with time.

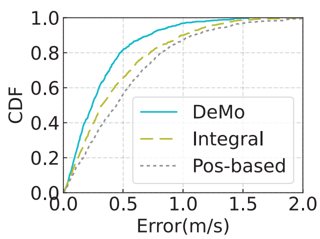

Fig. 15: Trolley speed estimation accuracy.

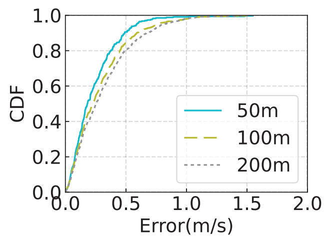

Fig. 16: Delivery path length with speed estimation error.

Table 6: Delivery path length distribution.

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

■ **Finding 6** *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.*

Positioning Accuracy. Fig. 17 compares positioning accuracy of using traditional logarithmic model [42], DeMo, DeMo which only relies on BLE without IMU (denoted as DeMo: BLE only), and the ideal localization based on BLE and ground-truth velocity calculated from passing two checkpoints (denoted as BLE+GTV). When only using BLE with the traditional logarithmic model, the mean positioning error is 3.22 m, while our new RSSI-distance model effectively reduces the mean positioning error to 2.86 m. By combining the 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. Additionally, we notice that for 2% of the checkpoints, DeMo's positioning error exceeds 6 m. This large error is primarily due to failures in receiving the broadcast BLE beacon packets and does not affect DeMo's operation in practice. Not surprisingly, BLE+GTV offers the best accuracy with a 1.70 m mean error, while GTV is not available in practice.

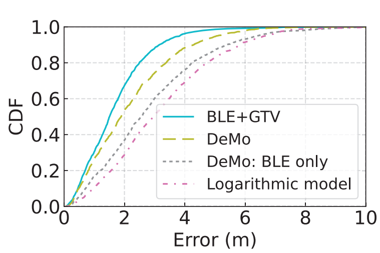

Fig. 17: Positioning accuracy.

■ **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 [30, 43].*

BLE Beacon Density. The beacon density affects the positioning accuracy. (1) For the evaluation of beacon density in typical areas, we randomly select one station that has a beacon density of 6m and adjust the beacon density to 12 m by temporarily disabling some beacons. As in Fig. 18, 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 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. (2) In addition to typical areas, several key areas are critical for DeMo's operation. For example, beacons deployed in shops (details in Sec. 3.2) are leveraged in DeMo's shop classification. The identified shop is essential in DeMo's delivery record and used to find shops with abnormally high violations. With three beacons, DeMo's store classification accuracy is 97%, which drops to 86% when there is one beacon. The classification errors largely result from trolleys' parking positions, which could be very close to nearby shops. To ensure reliable operation, DeMo adopts three beacons for shop classification.

BLE Beacon Broadcast Frequency. Another factor to affect localization accuracy is beacon broadcast frequency. Fig. 19 compares the positioning error with beacon broadcast intervals of 200 ms and 500 ms at the same station, while all other parameters are the same. The mean localization error increases from 2.17 m to 2.78 m, since DeMo's sensor receives more BLE packets with a smaller broadcast interval. Based on our 3-year operational experience, the average battery life of a BLE beacon with a 200 ms setting is 22 months. This leads to a maintenance cost (replacing failed beacons) of around 40 USD for each station per month.

IMU Sample Rate. In this experiment, we set the IMU sample rate to 500 Hz for data collection and then downsampled it to generate the IMU data at different frequencies. Fig. 20 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 offers a stable performance at 200 Hz. Similarly in Fig. 21, 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.

■ **Lesson 4** *DeMo aims at reliable monitoring under practical costs. It deploys sparse beacons for localization in most*

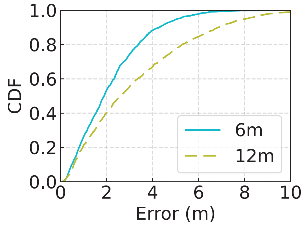

Fig. 18: BLE beacon density vs. positioning accuracy.

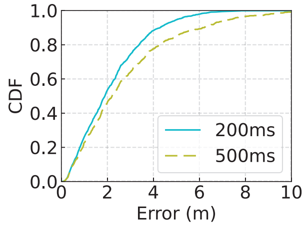

Fig. 19: BLE beacon broadcast frequency vs. positioning accuracy.

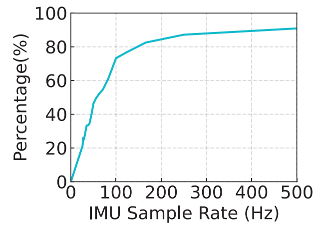

Fig. 20: IMU sample rate vs. road bump detection rate.

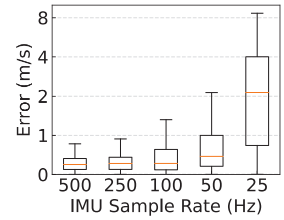

Fig. 21: IMU sample rate vs. speed error.

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.

6 Related Work

Prior Deployment Experiences. A few BLE-based [22, 30, 40, 70] and WiFi-based [27] localization systems were deployed in public indoor sites to offer localization and navigation services for clients. Recent studies [18, 19] reported deploying arrival detection for efficient delivery in large-scale instant delivery systems. In contrast, DeMo provides fine-grained monitoring of delivery violations toward better safety. A prior study [30] integrates BLE beacons and geomagnetic fields as fingerprints to offer localization services for shopping malls, while DeMo utilizes a labor-free RSSI-distance model to achieve similar localization accuracy. Other real-world existing BLE systems conducted presence detection [59, 60]. To our knowledge, there is very limited work on indoor delivery violation detection and regulation. During the operation of DeMo, we have learned valuable lessons that will contribute to future safety delivery.

Wireless Indoor Localization. Researchers have proposed various wireless indoor localization techniques for navigation [4,54], positioning [56,65], and assets tracking [35,72]. Their design principles could be classified as RSSI propagation model [10, 13, 26, 29, 31], fingerprinting [5, 11, 23, 28, 43, 55, 61], Angle-of-Arrival model [3, 12, 36, 37, 67], and Time-of-Flight [4, 58]. Although existing studies offer good positioning accuracy, they are commonly evaluated in small-scale environments. For example, Spotfi [37], ArrayTrack [67] and ToneTrack [68] achieve sub-meter localization accuracy by leveraging 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. In contrast, DeMo's in-the-wild operation validates the possibility of accurate localization via simple RSSI models with low deployment and maintenance costs, in addition to several unique lessons and insights.

IMU-Assisted Sensing System. These works [9, 71] analyze IMU's signal characteristics and extract the motion feature of humans to infer their posture, especially for Pedestrian Dead Reckoning [32]. This study [52] 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. DeMo leverages IMU reading to detect special road surfaces and further improves speed accuracy, and provides reliable positioning service.

7 Discussion

Limitations. (1) On-trolley sensor failure. We plan to design more reliable hardware with additional protection methods to ensure good device reliability. (2) Bypassing DeMo. DeMo covers 88% of the total deliveries. We will analyze delivery behaviors to understand possible ways of bypassing DeMo and further adopt corresponding mitigation to offer seamless monitoring coverage. (3) Delivery worker dissatisfaction. Although DeMo offers accurate violation detection as demonstrated by controlled experiments and feedback from MTR staff (Sec. 4.5), our small-scale interviews suggest that delivery workers perceived DeMo as a surveillance system, and so it was not received favorably.

Future Improvement and Deployment. We plan to improve DeMo with the following aspects. (1) Automatic parameter tuning. Delivery trolleys are generally still in front of the destination shops for 5 to 20 minutes when offloading products. This opportunity could be leveraged for fine-tuning our RSSI-distance model. (2) Future hardware design and deployment. We will improve our hardware reliability under rough handling and deploy DeMo in 10 more MTR stations.

8 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 for better coverage, effective change of human behaviors, better efficiency, and cost reduction. We hope that these lessons will contribute to future delivery monitoring systems.

9 Acknowledgements

We thank our shepherd and the anonymous reviewers for their insightful comments. This work was substantially supported by NSF China 62102332, CityU 21216822, CityU APRC 9610491, and CityU 11206023.

References

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

[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 *2020 28th European Signal Processing Conference (EUSIPCO)*, pages 1702–1706. IEEE, 2021.

[3] R. Ayyalasomayajula, A. Arun, C. Wu, A. Shaikh, S. Rajagopalan, Y. Hu, S. Ganesaraman, C. J. Rossbach, A. Seetharaman, E. Witchel, et al. LocAP: Autonomous millimeter accurate mapping of WiFi infrastructure. In *17th USENIX Symposium on Networked Systems Design and Implementation (NSDI 20)*, pages 1115–1129, 2020.

[4] R. Ayyalasomayajula, A. Arun, C. Wu, S. Sharma, A. R. Sethi, D. Vasisht, and D. Bharadia. Deep learning based wireless localization for indoor navigation. In *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, pages 1–14, 2020.

[5] P. Bahl and V. N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *Proceedings IEEE INFOCOM 2000. Conference on computer communications. Nineteenth annual joint conference of the IEEE computer and communications societies (Cat. No. 00CH37064)*, volume 2, pages 775–784. Ieee, 2000.

[6] T. A. Bentley. Slip, trip and fall accidents occurring during the delivery of mail. *Ergonomics*, 41(12):1859–1872, 1998.

[7] A. Bose and C. H. Foh. A practical path loss model for indoor wifi positioning enhancement. In *2007 6th International Conference on Information, Communications & Signal Processing*, pages 1–5. IEEE, 2007.

[8] A. Brajdic and R. Harle. Walk detection and step counting on unconstrained smartphones. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 225–234, 2013.

[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 *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–8. IEEE, 2016.

[10] D. Chen, K. G. Shin, Y. Jiang, and K.-H. Kim. Locating and tracking ble beacons with smartphones. In *Proceedings of the 13th International Conference on emerging Networking EXperiments and Technologies*, pages 263–275, 2017.

[11] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha. Fm-based indoor localization. In *Proceedings of the 10th international conference on Mobile systems, applications, and services*, pages 169–182, 2012.

[12] Z. Chen, Z. Li, X. Zhang, G. Zhu, Y. Xu, J. Xiong, and X. Wang. Awl: Turning spatial aliasing from foe to friend for accurate wifi localization. In *Proceedings of the 13th International Conference on emerging Networking EXperiments and Technologies*, pages 238–250, 2017.

[13] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan. Indoor localization without the pain. In *Proceedings of the sixteenth annual international conference on Mobile computing and networking*, pages 173–184, 2010.

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

[15] DeMo. IMU and BLE readings. https://github.com/Starry102/DeMo, 2023.

[16] DeMo. Parameters configuration. https://github.com/Starry102/DeMo/tree/main/train, 2023.

[17] J. Diebel. Representing attitude: Euler angles, unit quaternions, and rotation vectors. *Matrix*, 58(15-16):1–35, 2006.

[18] 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 Transactions on Networking*, 30(1):47–61, 2021.

[19] 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 *Proceedings of the 2021 ACM SIGCOMM 2021 Conference*, pages 705–717, 2021.

[20] P. M. Djuric, J. H. Kotecha, J. Zhang, Y. Huang, T. Ghirmai, M. F. Bugallo, and J. Miguez. Particle filtering. *IEEE signal processing magazine*, 20(5):19–38, 2003.

[21] L. D. Driver. Liquor delivery driver recovers $ 445,000 for fall on strip mall macadam. https://www.clarklawnj.com/liquor-delivery-driver-recovers-445000-for-fall-on-strip-mall-macadam/, 2020.

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

[23] R. Faragher and R. Harle. Location fingerprinting with bluetooth low energy beacons. *IEEE journal on Selected Areas in Communications*, 33(11):2418–2428, 2015.

[24] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan. Received-signal-strength-based indoor positioning using compressive sensing. *IEEE Transactions on mobile computing*, 11(12):1983–1993, 2011.

[25] Y. Gao, Q. Yang, G. Li, E. Y. Chang, D. Wang, C. Wang, H. Qu, P. Dong, and F. Zhang. Xins: The anatomy of an indoor positioning and navigation architecture. In *Proceedings of the 1st international workshop on Mobile location-based service*, pages 41–50, 2011.

[26] Y. Gu and F. Ren. Energy-efficient indoor localization of smart hand-held devices using bluetooth. *IEEE Access*, 3:1450–1461, 2015.

[27] D. Han, S. Jung, M. Lee, and G. Yoon. Building a practical wi-fi-based indoor navigation system. *IEEE Pervasive Computing*, 13(2):72–79, 2014.

[28] A. M. Hossain and W.-S. Soh. Cramer-rao bound analysis of localization using signal strength difference as location fingerprint. In *2010 Proceedings IEEE INFOCOM*, pages 1–9. IEEE, 2010.

[29] A. M. Hossain and W.-S. Soh. A survey of calibration-free indoor positioning systems. *Computer Communications*, 66:1–13, 2015.

[30] Y. Hu, F. Qian, Z. Yin, Z. Li, Z. Ji, Y. Han, Q. Xu, and W. Jiang. Experience: Practical indoor localization for malls. In *Proceedings of the 28th Annual International Conference on Mobile Computing And Networking*, pages 82–93, 2022.

[31] Y. Ji, S. Biaz, S. Pandey, and P. Agrawal. Ariadne: A dynamic indoor signal map construction and localization system. In *Proceedings of the 4th international conference on Mobile systems, applications and services*, pages 151–164, 2006.

[32] A. R. Jimenez, F. Seco, C. Prieto, and J. Guevara. A comparison of pedestrian dead-reckoning algorithms using a low-cost mems imu. In *2009 IEEE International Symposium on Intelligent Signal Processing*, pages 37–42. IEEE, 2009.

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

[34] W. Kang and Y. Han. Smartpdr: Smartphone-based pedestrian dead reckoning for indoor localization. *IEEE Sensors journal*, 15(5):2906–2916, 2014.

[35] 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 *2017 IEEE international conference on consumer electronics-Taiwan (ICCE-TW)*, pages 63–64. IEEE, 2017.

[36] A. Kludze, R. Shrestha, C. Miftah, E. Knightly, D. Mittleman, and Y. Ghasempour. Quasi-optical 3d localization using asymmetric signatures above 100 ghz. In *Proceedings of the 28th Annual International Conference on Mobile Computing And Networking*, pages 120–132, 2022.

[37] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti. Spotfi: Decimeter level localization using wifi. In *Proceedings of the 2015 ACM Conference on Special Interest Group on Data Communication*, pages 269–282, 2015.

[38] C. Li, M. Mirosa, and P. Bremer. Review of online food delivery platforms and their impacts on sustainability. *Sustainability*, 12(14):5528, 2020.

[39] M. Li, N. Liu, Q. Niu, C. Liu, S.-H. G. Chan, and C. Gao. Sweeploc: Automatic video-based indoor localization by camera sweeping. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(3):1–25, 2018.

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

[41] A. Mackey, P. Spachos, L. Song, and K. N. Plataniotis. Improving ble beacon proximity estimation accuracy through bayesian filtering. *IEEE Internet of Things Journal*, 7(4):3160–3169, 2020.

[42] 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 Transactions on Instrumentation and Measurement*, 60(11):3619–3628, 2011.

[43] J. Ni, F. Zhang, J. Xiong, Q. Huang, Z. Chang, J. Ma, B. Xie, P. Wang, G. Bian, X. Li, et al. Experience: pushing indoor localization from laboratory to the wild. In *Proceedings of the 28th Annual International Conference on Mobile Computing And Networking*, pages 147–157, 2022.

[44] T. G. of the Hong Kong Special Administrative Region. Wages and labour earnings. https://www.censtatd.gov.hk/tc/scode210.html, 2022.

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

[46] A. Opher, A. Chou, A. Onda, and K. Sounderrajan. The rise of the data economy: driving value through internet of things data monetization. *IBM Corporation: Somers, NY, USA*, 2016.

[47] G. Palshikar et al. Simple algorithms for peak detection in time-series. In *Proc. 1st Int. Conf. Advanced Data Analysis, Business Analytics and Intelligence*, volume 122, 2009.

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

[49] J. Racko, P. Brida, A. Perttula, J. Parviainen, and J. Collin. Pedestrian dead reckoning with particle filter for handheld smartphone. In *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–7. IEEE, 2016.

[50] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen. Zee: Zero-effort crowdsourcing for indoor localization. In *Proceedings of the 18th annual international conference on Mobile computing and networking*, pages 293–304, 2012.

[51] S. Rodriguez Garzon and B. Deva. Geofencing 2.0: taking location-based notifications to the next level. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 921–932, 2014.

[52] 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 *2018 IEEE international conference on communications (ICC)*, pages 1–6. IEEE, 2018.

[53] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang. Walkie-markie: Indoor pathway mapping made easy. In *NSDI*, volume 13, pages 85–98, 2013.

[54] S. Shen, N. Michael, and V. Kumar. Autonomous multi-floor indoor navigation with a computationally constrained mav. In *2011 IEEE International Conference on Robotics and Automation*, pages 20–25. IEEE, 2011.

[55] Y. Shu, K. G. Shin, T. He, and J. Chen. Last-mile navigation using smartphones. In *Proceedings of the 21st annual international conference on mobile computing and networking*, pages 512–524, 2015.

[56] M. L. Sichitiu and V. Ramadurai. Localization of wireless sensor networks with a mobile beacon. In *2004 IEEE international conference on mobile Ad-hoc and sensor systems (IEEE Cat. No. 04EX975)*, pages 174–183. IEEE, 2004.

[57] SINGAPORE. Death of delivery man who fell from platform at century square mall ruled a workplace misadventure. https://www.straitstimes.com/singapore/courts-crime/death-of-delivery-man-at-century-square-mall-ruled-a-workplace-misadventure, 2022.

[58] E. Soltanaghaei, A. Kalyanaraman, and K. Whitehouse. Multipath triangulation: Decimeter-level wifi localization and orientation with a single unaided receiver. In *Proceedings of the 16th annual international conference on mobile systems, applications, and services*, pages 376–388, 2018.

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

[60] THINKPROXI. Thinkproxi announces famous beale street implemented beacon technology. https://www.thinkproxi.com/thinkproxi-announces-famous-beale-street-implemented-beacon-technology/, 2017.

[61] X. Tian, R. Shen, D. Liu, Y. Wen, and X. Wang. Performance analysis of rss fingerprinting based indoor localization. *IEEE Transactions on Mobile Computing*, 16(10):2847–2861, 2016.

[62] R. v. Department of Water and Power. Making a delivery via a service elevator. https://caselaw.findlaw.com/ca-court-of-appeal/1764404.html, 1962.

[63] X. Wang, L. Gao, S. Mao, and S. Pandey. Csi-based fingerprinting for indoor localization: A deep learning approach. *IEEE transactions on vehicular technology*, 66(1):763–776, 2016.

[64] M. Werner, M. Kessel, and C. Marouane. Indoor positioning using smartphone camera. In *2011 international conference on indoor positioning and indoor navigation*, pages 1–6. IEEE, 2011.

[65] C. Wu, Z. Yang, Y. Liu, and W. Xi. Will: Wireless indoor localization without site survey. *IEEE Transactions on Parallel and Distributed systems*, 24(4):839–848, 2012.

[66] H. Wu, S. He, and S.-H. G. Chan. Efficient sequence matching and path construction for geomagnetic indoor localization. In *Proceedings of the 2017 International Conference on Embedded Wireless Systems and Networks*, pages 156–167, 2017.

[67] J. Xiong and K. Jamieson. ArrayTrack: A fine-grained indoor location system. In *10th USENIX Symposium on Networked Systems Design and Implementation (NSDI 13)*, pages 71–84, 2013.

[68] J. Xiong, K. Sundaresan, and K. Jamieson. Tonetrack: Leveraging frequency-agile radios for time-based indoor wireless localization. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, pages 537–549, 2015.

[69] J. Yang, S. Sidhom, G. Chandrasekaran, T. Vu, H. Liu, N. Cecan, Y. Chen, M. Gruteser, and R. P. Martin. Detecting driver phone use leveraging car speakers. In *Proceedings of the 17th annual international conference on Mobile computing and networking*, pages 97–108, 2011.

[70] Y. Yang, Y. Ding, D. Yuan, G. Wang, X. Xie, Y. Liu, T. He, and D. Zhang. Transloc: transparent indoor localization with uncertain human participation for instant delivery. In *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, pages 1–14, 2020.

[71] 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 *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 825–828. IEEE, 2015.

[72] 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 *Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007)*, pages 71–71. IEEE, 2007.

[73] M. Zhao, T. Chang, A. Arun, R. Ayyalasomayajula, C. Zhang, and D. Bharadia. Uloc: Low-power, scalable and cm-accurate uwb-tag localization and tracking for indoor applications. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(3):1–31, 2021.

A Appendix

A.1 Geomagnetic Field

When designing DeMo, we collected geomagnetic field (GMF) strength at different locations, including entry, exit, and open areas, within three stations. Our preliminary experiments validated significant GMF strength changes caused by operating trains. These changes are difficult to predict and eliminate. In normal indoor settings, *e.g.,* shopping malls, the geomagnetic field values are relatively stable without significant disruptions. Fig. 22 compares the collected GMF strength values at a fixed location (*e.g.,* entrance) in an MTR station and a shopping mall, respectively. As a result, we decided not to leverage geomagnetic field sensing in DeMo.

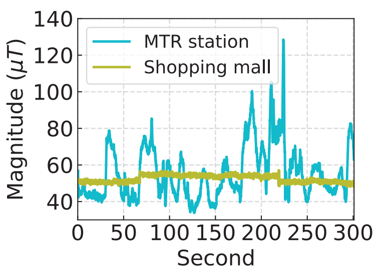

Fig. 22: Examples of GMF strength change with time at a shopping mall and MTR station.

A.2 RSSI-distance Models Comparison

Crowd obstruction and reflection cause severe signal strength degradation (or even signal loss), deviating from the traditional logarithmic model. Therefore, we instead use a polynomial function to model the effect of crowds on signal strength. Table 7 lists the average positioning accuracy of 4 different polynomial models with degrees ranging from 1 to 4. The parameters of the RSSI-distance model were trained using data from one station and applied to other stations without retraining. Models with a higher polynomial degree are prone to overfitting, while those with a lower polynomial degree exhibit unstable accuracy due to the influence of subway crowds. Consequently, we have opted for a cubic polynomial function as it delivers superior accuracy compared to other polynomial orders.

Table 7: Mean localization accuracy under different polynomial orders at two MTR stations.

Polynomial Orders	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

A.3 Positioning Accuracy Validation

DeMo's training data for its RSSI-distance model is collected in one MTR station, followed by a one-time parameter tuning process. Then we validate this RSSI-distance model across the remaining stations. To demonstrate the robustness of our model, we present the overall mean localization errors (solely relying on BLE without IMU integration) in Table 8. The validation process is conducted via control experiments, following Sec. 5.1. In most stations, the positioning accuracy closely matches the initial station used for model training. However, two subway stations exhibit poorer positioning accuracy (3.68 m and 3.83 m). Compared to most subway stations, which typically feature long, narrow delivery areas, these two stations have unique layouts with larger open spaces. This distinct layout can result in reduced positioning accuracy within those open areas. Besides, we noticed more severe beacon losses in these two stations which inevitably affect the positioning accuracy.

Table 8: Positioning accuracy in 12 stations.

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

A.4 Glossary of Main Parameters

Table 9 lists DeMo's main parameters, which are crucial for the system's functionality. t_{sw}, R_{th}, n and p_w are empirical parameters. Coefficients γ_0 through γ_3 are trained via simulation experiments, with the detailed training method available at the link [16]. Besides, a_{std} refers to the study [50].

A.5 Questionnaire

The questionnaire consists of six multiple-choice questions, each utilizing a 5-point scale ranging from 5 (strongly agree) to 1 (strongly disagree). The detailed questions are: 1. please select the option that best represents your level of satisfaction with the DeMo system, 2. please select the option that best describes your perception of the ease of use of the DeMo device, 3. please select the option that best represents your

Table 9: Glossary of main parameters.

Parameters	Values	Description
t_{sw}	4 s	A sliding window
R_{th}	-80 dBm	RSSI threshold
γ_0	94.8951	Coefficient of the cubic function
γ_1	5.8301	Coefficient of the cubic function
γ_2	0.0811	Coefficient of the cubic function
γ_3	0.0005	Coefficient of the cubic function
n	2, 8	# of IMU reading peaks
a_{std}	0.01 g	Standard deviation of the IMU
p_w	60%	# of weighted particles

assessment of the DeMo system's effectiveness in reducing safety violations, 4. please select the option that best reflects your perception of the DeMo system's accuracy in detecting speeds, 5. please select the option that best describes the extent to which the DeMo system has reduced your workload, and 6. please select the option that best represents how frequently you have encountered sensor damage issues with the DeMo system. The feedback from 20 safety staff in 12 MTR stations is demonstrated in Fig. 14.