Using Machine Learning to Improve Accuracy and Robustness of Indoor Positioning under Practical Usage Scenarios

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Abstract— **Indoor Positioning Systems (IPSs) can increase productivity in both office and industrial settings. They continue to become more accurate and robust as the advent of machine learning enables them to overcome the limitations of traditional positioning techniques. Despite this, the mainstream incorporation of IPS is currently hindered by significant infrastructure cost, especially for areas that cannot attain sufficient wireless coverage due to budget or environmental constraints. This paper therefore explores the use of machine learning for infrastructure-limited smartphone-based localization while adhering to practical constraints. The performance of the trained models was compared to that of conventional multilateration while also considering the effect of phone placement on positioning accuracy. Experimental results showed that the model trained under harsher conditions proved to be the most robust for both handheld and pocket mobile tests.**

I. Introduction

Indoor localization is the act of tracking assets within interior spaces, where the lack of line-of-sight satellite signals diminish the accuracy of Global Navigation Satellite System (GNSS) technologies. An Indoor Positioning System (IPS) typically consists of mobile tags capable of communicating wirelessly with reference nodes strategically installed around the site. From these, the measurements are collected and used by the positioning engine to determine the location of the target. As data-driven automation becomes commonplace across various industries, employing an IPS to provide real-time asset tracking can offer several benefits to productivity. This data can provide location-based services that can help keep accurate inventory, aid in personnel and visitor access control, and identify workflow trends and bottlenecks.

Even with these potential advantages, there exists concerns that cause hesitancy towards IPS adoption. Indoor positioning often necessitates purchasing additional hardware, which can incur significant monetary and labor costs. Sufficient reference nodes must be installed for the IPS to provide acceptable coverage and accuracy and would require maintenance from knowledgeable personnel. Subsequently, workplace procedures need to be carefully adjusted so that the tags are efficiently integrated into the workflow without disrupting employees. Nevertheless, the positioning accuracy during deployment may not be as advertised. Wireless technologies are inherently susceptible to electromagnetic noise, environmental clutter, and muti-path effects. This is especially true for Wi-Fi and Bluetooth Low Energy (BLE), as they rely on the Received Signal Strength Indicator (RSSI) values, which are known to be exceedingly sensitive to minute changes.

The proliferation of machine learning in adjacent fields has attracted a similar interest in using trained models to improve current indoor localization techniques. Studies have proposed machine learning solutions capable of determining the location of the target with varying degrees of granularity, from room-based classification [1] to coordinate-based regression [2]. Fingerprinting approaches [3-5] are notably popular as machine learning models can capture the underlying signal distribution based on the collected data from multiple transmitters available on the site.

Most proposed solutions in literature consider locations that allow for enough beacons to be installed to achieve sufficient wireless coverage. However, this may not be possible for certain spaces, as it may be constrained by the company's budget or the location's physical layout. Machine learning solutions have proven that they can infer the underlying signal distribution and yield superior accuracy in setups with satisfactory coverage. It can thus be extrapolated that they may be able to obtain acceptable positioning accuracy under limited infrastructure, as shown in [6], where machine learning was used to improve single reference positioning accuracy given a pre-determined route. Therefore, the use of machine learning for improving infrastructure-limited IPSs merits exploration. This paper explores the development and performance of machine learning models for IPS operating under a practical usage scenario. To minimize infrastructure cost, the IPS hardware was limited to a few ceiling-mounted BLE beacons and smartphones of personnel. Experiments were then conducted to compare the trained model to traditional positioning methods.

This paper consists of four further sections. Section II details the setup and constraints of the IPS used in the experiments. Section III elaborates on the methodologies used for positioning, which consists of the proposed machine learning model and traditional positioning techniques. Section IV discusses and analyzes the results from experimentation proper and Section V contains the conclusion.

II. Infrastructure-Limited Positioning

Most literature involving machine learning for indoor positioning assume there is sufficient wireless coverage in the location, but there may be cases where it may not be feasible to install enough reference nodes due to floorplan or

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budget constraints. Therefore, this paper explores a scenario with limited infrastructure and describes the circumstances in this section.

The test site (Figure 1) is situated in a 40 m x 15 m office environment, where employees can traverse along the route indicated by the dotted line. Five BLE beacons are installed on accessible points on the ceiling. As opposed to conventional placement, where multiple beacons would be placed to form cells, the beacons are placed on the same side of the route at roughly 10 m apart. To ease adoption and remove the need for additional hardware tags, the system makes use of a smartphone app that personnel can install on their phones. The app will periodically scan for the transmitting beacons, and the results are sent over to a central server where either conventional methods or machine learning is used to calculate the phone's position.

Deliberately limiting IPS infrastructure has the likelihood of negatively affecting the accuracy compared to that of a conventional IPS setup. Machine learning may improve accuracy to an acceptable level, but its design must also consider the practical system limitations so as to not report accuracy that is higher than what can be obtained under real-life conditions. This section details the constraints considered for this scenario on both the wireless reference nodes and the smartphone.

A. Practical Constraints for Wireless Technologies

Wi-Fi and BLE are considered the more popular wireless technologies used in indoor positioning for both research and commercially available off-the-shelf systems. Both are becoming increasingly ubiquitous, as various consumer smart devices rely on BLE for short-range wireless communication and Wi-Fi Access Points (APs) can be found in most buildings to provide internet connection.

Studies have recommended setups with existing Wi-Fi APs serving as reference nodes and personal smartphones serving as tags since this removes the need for additional hardware. While this appears to be feasible in theory, there are a few practical limitations that remain unaddressed. The installed Wi-Fi APs are optimized for network coverage, not necessarily for localization. To obtain a stable connection, a device just needs to be in proximity to a single AP. On the other hand, a device must be within communicable range of multiple reference nodes to obtain an accurate position estimate. This means that the APs are installed at distances farther apart than what is desirable for localization purposes and there may be certain cases where the APs may not appear at all in scan results. This issue is compounded by the recent scanning limitations of Android phones, where smartphones running Android 8.0 and above throttle Wi-Fi scanning in the background [7]. Some studies have circumvented this restriction by enabling developer options, but typical users cannot be expected to enable this setting.

Given such limitations, this paper considers BLE instead. BLE beacons, unlike Wi-Fi APs, are low cost and easy to install. More importantly, BLE does not have such drastic scanning limitations, so smartphones can run an app that can collect BLE scans in the background as the users go about normal usage.

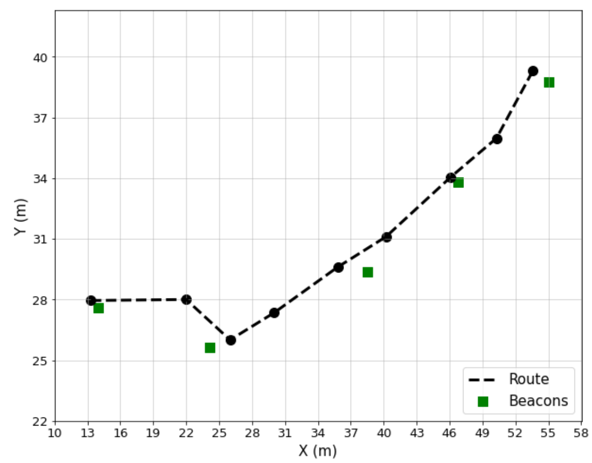

Figure 1. Test Site Plot of the Infrastructure-Limited IPS

B. Practical Constraints for Smartphone-based Positioning

Literature proposing the use of smartphones for indoor positioning has gained traction in recent years. These devices have become increasingly ubiquitous such that it can be a reasonable assumption for most employees in a workplace to have one. More importantly, smartphones are mobile computing devices with moderate processing power and a suite of onboard sensors. In the context of indoor positioning, they can thus offer additional advantages such as data pre-processing or position refinement via fusion of additional sensor data.

At the minimum, smartphones can conduct BLE scans at regular intervals in the background while allowing users to proceed with normal usage. The scan results consist of a list of nearby BLE devices and their respective RSSI values, which are an indication of their proximity to the smartphone. By considering multiple RSSI values from beacons whose locations are known, the position engine is able to estimate the target's location. However, RSSI values are known to be unstable, as they are sensitive to interference, electromagnetic noise, and environmental conditions. It is possible for obtained values to drastically fluctuate, especially when the target is in motion.

It is for this reason that many RSSI-based indoor positioning papers in literature consider an ideal case where the beacons are installed overhead while the smartphone is held flat with the screen face up in the target's hand [8, 9]. This method increases the likelihood of line-of-sight measurements and minimizes jitter caused by motion, allowing the phone to obtain stable RSSI values. While it is understandable to want to remove confounding factors in order to accurately gauge the effectiveness of the proposed positioning solution, this simplification can result in accuracies that are higher than what can be achieved under realistic conditions.

In workplaces, employees would tend to keep their phones in their pockets. This placement can diminish the quality of the BLE scan results as clothing and the human

TABLE I. COMPARISON OF RSSI READINGS COLLECTED AT THE HANDHELD AND POCKET PHONE PLACEMENTS

Direction	Maximum RSSI (dBm)		Average RSSI (dBm)		Standard Deviation		Percentage of Missing Readings	
	Handheld	*Pocket*	*Handheld*	*Pocket*	*Handheld*	*Pocket*	*Handheld*	*Pocket*
North	-53	-50	-69	-72	18.62	17.34	26.32	25.77
Northwest	-52	-44	-70	-66	18.48	20.89	26.32	26.32
West	-52	-47	-72	-70	18.35	22.57	28.81	35.71
Southwest	-51	-49	-77	-75	19.68	18.41	41.38	33.90
South	-53	-52	-75	-77	19.17	20.01	36.21	41.82
Southeast	-57	-57	-74	-75	16.57	16.71	27.59	31.03
East	-57	-59	-75	-73	16.93	15.90	29.82	25.86
Northeast	-49	-53	-68	-76	19.55	19.00	25.86	37.29
Overall	-49	-44	-72	-73	18.80	19.13	30.11	31.40

body block signals from the smartphone's antenna. To illustrate this discrepancy between the two different phone placements, data was collected experimentally using a BLE beacon mounted on a ceiling that is 2.65 m high. For both placements, a person stood 2.5 m away from the beacon and collected beacon scan data over a one-minute duration while facing eight different directions. The RSSI values received from the specific beacon were then filtered from the scan results, and should the beacon not be listed in a scan result, a minimum value of -100 dBm is assumed.

Table I lists the maximum RSSI, average RSSI, standard deviation, and percentage of missing readings for each phone placement across the eight different orientations. As seen in the overall statistics, scans with the phone placed in the pants pocket have a lower average RSSI, a higher standard deviation and more missing readings. While there are instances when the pocket placement yields a better statistic compared to the handheld placement, this can be attributed to the pocket placement yielding fewer readings for that orientation. This in fact further illustrates decreased stability in the RSSI readings when the phone is placed in the pocket. The handheld statistics yielded closer values in adjacent orientations, as opposed to the pocket statistics where readings taken from the northwest and west orientations are vastly different. Most importantly, the BLE beacon appears less in scan results taken when the phone is in the pocket. This is significant as conventional indoor localization algorithms typically take the strongest available readings that appear in a scan result. Should a nearby beacon not appear in the scan, the positioning engine will use other beacons that are farther away, which can lead to a less accurate position estimate and can cause a jump in the overall trajectory when the BLE beacon reappears in subsequent scan results.

As suspected, the experimental results show that readings from the handheld placement are more stable than that of the pocket placement and can therefore yield a higher positioning accuracy than what can be expected in actual practice. Thus, it is crucial that a more realistic placement such as in the pants pocket is also considered in the development and evaluation of indoor positioning solutions.

III. METHODOLOGY

The BLE scan results from the smartphone are sent over to the positioning engine, which is running on a central server. At each timestep, the MAC addresses of the installed beacons shown in Figure 1 are filtered from the received list and the corresponding RSSI values are then used by the engine. As this paper proposes using a machine-learning based solution, training and test datasets were collected from the site by traversing the designated route. This section describes two methods that the positioning engine can use in calculating the estimate: the conventional BLE-based multilateration and the proposed machine learning method.

A. Conventional BLE-based Multilateration

Traditional indoor positioning methods typically make use of measurements from multiple beacons. As their positions are known, it is possible to estimate the approximate location of the target based on the distance of the target to each of the beacons. The infrastructure-limited setup utilizes RSSI values from BLE beacons. To mitigate the inherent instability of the measurements, the readings were first stored in a moving window. The RSSI measurement from one beacon at time t is the mean of the window values. This paper uses the Weighted Path Loss scheme in [10] to calculate the conventional BLE estimates. The RSSI value received from a beacon i at time t can be expressed as the following formula:

$$RSSI_{i,t} = PL_0 + 10\alpha \log(d_{i,t}) \quad (1)$$

where PL_0 is the path loss coefficient, α is the path loss exponent, and $d_{i,t}$ is the distance between the smartphone and the beacon. Based on (1), $d_{i,t}$ can be expressed as a function of the RSSI value:

$$d_{i,t} = 10^{\frac{RSSI_{i,t} - PL_0}{10\alpha}} \quad (2)$$

At best, the smartphone can receive RSSI values from all N transmitting beacons. The approximate distances from each beacon from the smartphone can be derived from (2). The positioning engine then calculates the weight $w_{i,t}$ of each beacon as a function of its distance:

$$w_{i,t} = \frac{1}{d_{i,t}} \times \frac{1}{\sum_{i=1}^{N} \frac{1}{d_{i,t}}} = \frac{1}{d_{i,t} \sum_{i=1}^{N} \frac{1}{d_{i,t}}} \quad (3)$$

By performing a weighted sum of the beacon positions, the positioning estimate derived via conventional multilateration $p_{t,MTL}$ is thus given by:

$$p_{t,MTL} = (x, y)_{t,MTL} = \sum_{i=1}^{N} w_{i,t} (x_i, y_i) \quad (4)$$

B. Machine Learning Model

Given the RSSI values of the installed BLE beacons, the machine learning model must be able to predict the target's approximate position. This task is therefore a regression problem, and so the model's output must be x- and y-coordinates. As for the inputs, the model may be able to discern the target's location given the RSSI value and location of the strongest beacon. Similar to conventional multilateration, the machine learning model makes use of averaged RSSI values from the known beacons. However, unlike the traditional method, the machine learning model only takes in the RSSI value, x-coordinate, and y-coordinate of the BLE beacon with the strongest signal.

Data was collected from the site for both handheld and pocket configurations by traversing through the set route in Figure 1. A stopwatch was used to note down times when the user arrives at the route checkpoints, indicated by the black dots along the path. Afterwards, the timestamps were matched to the data to generate the ground truth. This study opted to use machine learning instead of deep learning, as the latter requires tremendous amounts of data. Intensive data collection would significantly increase the manpower cost of the proposed solution and would go against the rationale of this budget-constrained scenario.

Scikit-learn [11] was used to train and evaluate the machine learning models. The training phase utilized a 75%-25% training-validation split for both handheld and pocket configurations. Both trials had identified Random Forest as the most accurate regression algorithm, which is supported by other regression problems in the positioning context [6]. Using cross-validation, the models performed best when they had a maximum depth of 10 and consist of 100 estimators. Finally, two regressors were trained under these parameters for both the handheld and pocket configurations to study the impact of phone placement on positioning performance.

IV. Results and Discussion

The results in this section were obtained via two separate test sets collected alongside the training sets during the data collection exercise described in Section III-B. Each test set was a mobile test that involved the user traversing the route shown in Figure 1, with one set collected when the phone was held in the person's hand, and the other set when the phone was placed in the pants pocket. RSSI-based positioning via Multilateration (MTL), the machine learning model trained with handheld data (HML), and the machine learning model trained with pocket data (PML) were compared against one another using metrics commonly used in machine learning and indoor positioning. To mitigate the inherent instability of RSSI, estimates from all three methods were averaged using a moving window as a post-processing step.

The scenario described in Section II contains both realistic and situational limitations that can hamper performance and decrease the accuracy for all methods. It is important to study the effects of these constraints when comparing traditional multilateration to the machine learning models to provide a clearer list of pros and cons when deploying each method. In particular, the effect of the phone placement on positioning accuracy bears merit for study. The findings from Section II-B indicate that RSSI values can vary drastically depending on where the phone is kept, and as such, it is important to observe how the proposed positioning methods can be affected by this factor.

A. Evaluation Criteria

A combination of machine learning and indoor positioning metrics was employed to appraise the localization methods. Positioning accuracy was determined by calculating Euclidean distance between the ground truth positions and the position estimates. For example, the error of a position estimate derived from multilateration at time t can be expressed as:

$$Err_{t,MTL} = \sqrt{\left(x_{t,GT} - x_{t,MTL}\right)^2 + \left(y_{t,GT} - y_{t,MTL}\right)^2} \quad (5)$$

where $x_{t,GT}$ and $y_{t,GT}$ are the ground truth position coordinates at time t, and $Err_{t,MTL}$, $x_{t,MTL}$, and $y_{t,MTL}$ are the error, and calculated position coordinates using multilateration at time t respectively. The mean and maximum errors in meters were subsequently derived from (5). The former was considered as a measure of overall accuracy while the latter was considered to gauge the effect of RSSI instability.

The Coefficient of Determination (R^2) measures the correlation between the position estimates to the ground truth, ranging from 0 to 1.0. Given N recorded measurements, the coefficient of determination for MTL (R^2_{MTL}) is given by:

TABLE II. EXPERIMENTAL RESULTS FOR HANDHELD AND POCKET TEST SETS

Criteria	Mobile Test – Handheld			Mobile Test – Pocket		
	MTL	*HML*	*PML*	*MTL*	*HML*	*PML*
Mean Error (m)	2.21	2.09	1.84	2.43	2.98	1.87
Max Error (m)	5.82	5.92	7.06	8.65	12.47	8.05
R^2	0.94	0.95	0.96	0.94	0.88	0.94
$ACC_{1.0}$ (%)	22.22	27.78	30.77	19.69	22.83	43.31
$ACC_{5.0}$ (%)	97.86	95.30	94.87	94.49	83.07	92.13
$ACC_{10.0}$ (%)	100.00	100.00	100.00	100.00	96.85	100.00

$$R^2_{MTL} = 1 - \frac{\sum_{i=1}^{N}\left(p_{i,GT} - p_{i,MTL}\right)^2}{\sum_{i=1}^{N}\left(p_{i,GT} - \overline{p_{GT}}\right)^2} \tag{6}$$

where $p_{i,GT}$ is a ground truth position estimate, $\overline{p_{GT}}$ is the mean of the ground truth estimates, and $p_{i,MTL}$ is an MTL position estimate.

Lastly, this study considers the accuracy metric from [6]. By studying the percentage of measurements that have error below a certain distance, insight into the positioning method's effectiveness can be gained in a more granular manner. $ACC_{M,MTL}$ in (7) is therefore the percentage of MTL estimates whose errors that fall below M m:

$$ACC_{M,MTL} = \frac{\sum_{i=1}^{P}\left[\left(p_{i,GT} - p_{i,MTL}\right) \leq M\right]}{P} \times 100\% \tag{7}$$

where $\sum_{i=1}^{P}\left[\left(p_{i,GT} - p_{i,MTL}\right) \leq M\right]$ is the number of estimates with errors below M m, and P is the total number of test readings. This study considers $ACC_{1.0}$, $ACC_{5.0}$, and $ACC_{10.0}$, or the percentage of measurements below 1.0 m, 5.0 m, and 10.0 m error. In addition, the position error distribution curves for each method were plotted.

B. Handheld Test Results

Table II contains the results of the mobile test taken with the phone held in the person's hand. All three methods performed reasonably well, with at least 90% of estimates falling below 5 m error. This can be attributed to the phone's placement, as holding it with the screen facing upwards at chest level can allow it to receive more high quality BLE scan results. In addition, the handheld placement can help stabilize the phone during movement and minimize jitter.

MTL and HML have comparable results, with the HML yielding a lower mean error of 2.09 m compared to that of MTL's 2.21 m. The HML also has a higher $ACC_{1.0}$, with 27.78% of readings falling below 1 m error as opposed to the 22.22% for MTL. However, the maximum error for HML is slightly higher at 5.92 m. This is supported by the plotted error distribution curve shown in Figure 2, where HML has a longer tail. Nevertheless, it is notable that HML achieved an R^2 of 0.95 and 56.83% of estimates have errors below 2 m.

Despite being trained using data with a different phone placement, the PML was able to yield comparable results to that of MTL and HML. It has the lowest mean error of 1.84 m and approximately 85.04% of readings fell below 3 m error (Figure 2). Although, it has the highest maximum error at 7.06 m and an $ACC_{5.0}$ of 94.87%.

C. Pocket Test Results

The test results for the mobile test using the pocket placement shown in Table II exhibit an increase in error and decrease in the ACC metrics across all methods. As the

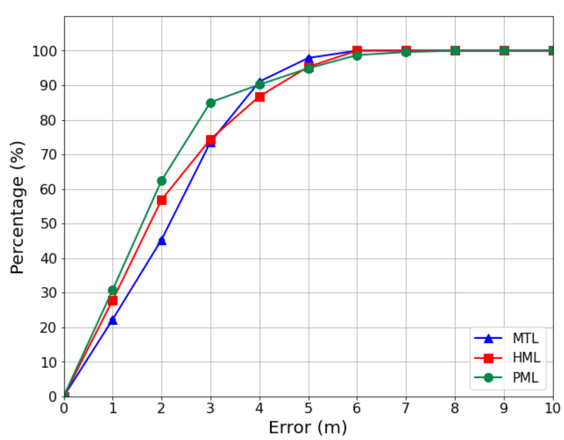

Figure 2. Error Distribution Curves for Handheld Test

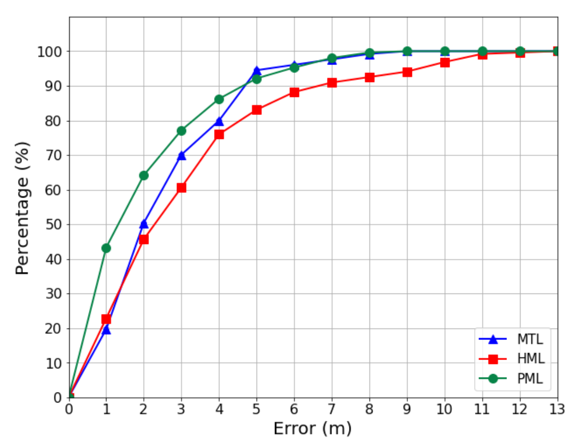

Figure 3. Error Distribution Curves for Pocket Test

phone is placed in the pants pocket, it may not be able to consistently communicate with nearby beacons due to the occlusion from clothes and the human body. In addition, motion is more pronounced as the pants pocket moves back and forth, thereby increasing jitter and RSSI uncertainty. These harsher conditions negatively affect the BLE scan results, resulting in more unstable RSSI values and the occasional exclusion of beacons in scans.

Upon comparing traditional MTL to PML, it appears that machine learning adjusted better to these harsh conditions despite having only a small amount of training data. The PML model has a markedly lower mean error of 1.87 m compared to MTL's 2.43 m and is able to lower maximum error to 8.05 m. Most notably, 43.31% of PML's estimates fall below 1 m error. It should also be mentioned that PML's performance under the more ideal handheld phone placement is comparable to MTL's, which may indicate that training with harsher data has made PML more robust.

On the other hand, HML was the most affected out of the three models, exhibiting the most drastic increase in error when compared to its performance in the handheld test. It reported the highest mean error of 2.98 m, the highest maximum error of 12.47 m, and the lowest R^2 of 0.88. HML's error distribution curve can also be observed to be markedly lower than that of MTL and PML in Figure 3, with a longer tail reaching beyond the 10-m mark. This decrease in performance must be kept in mind as most works in literature typically collect data under ideal conditions. Should there be additional constraints during practical deployment, the performance of a machine learning solution can drastically differ from what was reported during the initial, more contained trials.

V. Conclusion

Indoor positioning has the potential to promote comprehensive real-time location-based services that can further increase productivity in both office and industrial spaces. Currently, IPS adoption is hindered by the significant infrastructure cost, as certain locations may face monetary or inherent floorplan limitations. The use of machine learning has the potential to vastly improve the accuracy of an IPS with limited infrastructure, but it is crucial to identify and replicate practical constraints when training the machine learning model. Specifically, in the case of smartphone-based positioning, it is crucial to consider realistic phone placements aside from the ideal case where the phone is held in the person's hand.

The results in this paper show that machine learning models can perform better than traditional positioning techniques under practical, real-life constraints. The PML managed to outperform MTL for both the handheld and pocket test cases, reporting a mean error of 1.87 m and keeping 43.31% of estimates below 1 m error for the harsher pocket mobile test. On the other hand, the performance of MTL can be seen as comparable to that of HML in the handheld mobile test. This implies that conventional MTL can still be employed if the handheld placement can be guaranteed, such as when the phone can be mounted on the unobstructed surface of a robot or an automated guided vehicle.

While not the best performer, the HML's performance was particularly noteworthy as it illustrated the resulting discrepancy in accuracy when a machine learning model is trained under conditions more ideal than what can be done in practice. The drop in accuracy was an indication that the model was not as robust because it was accustomed to stable data. This is contrasted by PML, which was trained using BLE scan results of lower quality yet could still garner comparable statistics in the handheld test. As avenues for future work, filters can further improve performance by performing outlier detection and jumping mitigation since the machine learning models were observed to have slightly higher maximum errors. The smartphone's other sensors can also be utilized to improve accuracy, either through sensor fusion or as additional inputs to the machine learning model's design.

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