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PortLoc: A Portable Data-driven Indoor Localization Framework for Smartphones

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Abstract: For indoor navigation and localization, fingerprinting is an appealing technique that is low-cost, highly accurate, and inherently resilient to multipath effects. However, most prior research on fingerprinting for indoor localization does not consider device heterogeneity (i.e., the same smartphone is used for training and testing). In the real-world, users utilize diverse smartphones, leading to degradation in performance of fingerprinting-based localization techniques when ported across devices. We propose a portable, light-weight fingerprinting framework that is resilient to device heterogeneity. An in-depth analysis of our framework with state-of-the-art localization techniques in a variety of indoor environments demonstrates its effectiveness.

Keywords: Indoor Localization, Indoor Positioning, Device Heterogeneity, Device Portability, Smartphone Heterogeneity, Smartphone Portability,

1 Introduction

THE arrival of Global Positioning System (GPS) technology has revolutionized the way we navigate around the world. Today, every smartphone comes with a built-in GPS that is invaluable for outdoor navigation. Indoor localization technology holds a similar potential to disrupt the way we navigate within spaces that are unreachable by GPS, e.g., malls, buildings, and tunnels. Several startups such as IndoorAtlas, Target (Shopkick), and Zebra have already started to provide services that can help customers find products within a store [1].

Unlike GPS for outdoor localization, no standardized solution exists for indoor localization. Therefore, a myriad of techniques have been developed that use various sensors and radio frequencies. Some commonly utilized radio signals are Bluetooth, RFID, UWB (Ultra-Wide Band), and Wi-Fi [2]. Among these, Wi-Fi based indoor localization has been the most widely researched, due to its low setup costs and easy availability. Indeed, Wi-Fi access points are already deployed in most indoor locales and all smartphones support Wi-Fi connectivity.

Despite the advantages of Wi-Fi based indoor localization, there are also some drawbacks. Wi-Fi signals suffer from weak wall penetration, multipath fading, and shadowing effects. These challenges make it difficult to establish a direct mathematical relationship between Received Signal Strength Indicator (RSSI) and distance from Wi-Fi Access Points (WAPs). These issues have served as a motivation to use fingerprinting-based techniques. Fingerprinting is based on the idea that different locations indoors exhibit a unique signature of WAP RSSI values. Due to its independence from the RSSI-distance relationship, fingerprinting overcomes some of the aforementioned drawbacks associated with Wi-Fi based indoor localization.

Fingerprinting is usually carried out in two phases. In the first phase (offline or training phase), the RSSI values for visible WAPs are collected along paths of interest. The resulting database of values may further be used to train models (e.g., machine learning-based) for location estimation. In the second phase (online or testing phase), the models are used to predict the location of a user based on visible WAP RSSIs.

A majority of the literature that utilizes fingerprinting employs the same smartphone for (offline) data collection and (online) location prediction [3]-[5]. This assumes that in a real-world setting, users would have access to the same smartphone as the one utilized in the offline phase. Today's diverse smartphone market, consisting of various brands and models, largely invalidates such an assumption. In reality, the smartphone user base is a distribution of heterogeneous mobile devices that vary in antenna gain, Wi-Fi chipset, antenna shape, OS version, etc.

Recent works have shown that the perceived RSSI values for a given location captured by different smartphones can vary significantly [6]. This variation degrades the localization accuracy achieved through conventional fingerprinting. Therefore, there is a need for portable, device heterogeneity-aware fingerprinting techniques.

In this paper, we present a robust, lightweight, data-driven Wi-Fi RSSI-based fingerprinting framework (PortLoc) that is portable across heterogeneous mobile devices with minimal accuracy loss. The main contributions of our work are:

- we conduct an in-depth analysis of fingerprinted data to highlight the importance of using data-driven pattern matching approaches for heterogeneous device-based indoor localization;
- we identify computationally inexpensive metrics that can be used to compare fingerprint features;
- we design the PortLoc framework for truly portable Wi-Fi fingerprinting-based indoor localization;
- we create a set of benchmarks by collecting fingerprints with multiple heterogeneous devices across buildings, for testing the performance of PortLoc against state-of-the-art localization techniques.

2 Related Work

A significant body of work has been devoted to addressing the challenges associated with Wi-Fi fingerprinting-based indoor localization. Recent work on improving Wi-

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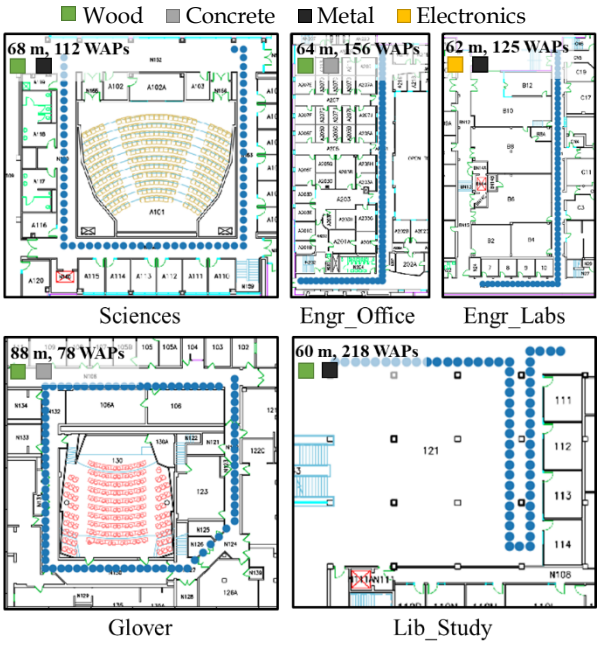
Fi fingerprinting exploits the increasing computational capabilities of smartphones. For instance, more sophisticated Convolutional Neural Networks (CNN) and ensemble learning are being used in smartphones to improve indoor localization accuracy [4]-[5]. One of the concerns with utilizing such techniques are the severe energy limitations on mobile devices. Pasricha et al. [3] proposed an energy efficient fingerprinting-based technique. However, all prior work, including [3], is plagued by the same major drawback, i.e. the lack of device heterogeneity across the offline and online phases. This drawback leads to localization solutions that are untested for real-world scenarios.



(a)

Smartphone	Chipset	Android
OnePlus 3 (OP3)	Snapdragon 820	8.0
LG V20 (LG)	Snapdragon 820	7.0
Moto Z2 Force (MOTO)	Snapdragon 835	8.0
Samsung S7 (SS7)	Snapdragon 820	7.0
HTC U11 (HTC)	Snapdragon 635	8.0
BLU Vivo 8 (BLU)	MediaTech Helio P10	7.0

(b)

Figure 1. (a) Benchmark paths for indoor localization showing path length, number of WAPs, and key environmental features, (b) Smartphones used in experiments

In general, devices used by localization solution providers to collect Wi-Fi fingerprints across locations in the offline phase are different from the devices owned by the users in the online phase. Some of the known factors that introduce device heterogeneity include different Wi-Fi antennas, smartphone design materials, hardware drivers, and the OS. Techniques to overcome this issue fall into two major categories: calibration-based methods and calibration-free methods.

The simplest calibration-based approach for heterogeneous device calibration is to acquire RSSI values and location data manually for each new device [8], which is however not very practical. Once RSSI information is collected, manual calibration can be performed through transformations such as weighted-least square optimizations and time-space sampling [9]. These techniques can be aided by crowdsourcing schemes. However, such approaches suffer from accuracy degradation [10].

In calibration-free fingerprinting, the fingerprinting data is translated into a standardized form that is portable across devices. One such approach, known as Hyperbolic Location fingerprint (HLF) [11] uses the ratios of individual WAP RSSI values to form the fingerprint. Unfortunately, HLF significantly increases the dimensionality of the training data in the offline phase. The Signal Strength Difference (SSD) approach [7] reduces the dimensionality by taking only independent pairs of WAPs into consideration. But this approach causes accuracy deterioration. Improvement in accuracy through Procrustes-based shape analysis and uniform scaling of RSSI values was proposed in [6]. The RSSI values are standardized through a Signal Tendency Index (STI), while maintaining the dimensionality of the training data. The STI based technique was shown to perform better than SSD and HLF. Since STI is used in conjunction with Weighted Extreme Learning Machines (WELMs) for best performance, it is a computationally expensive technique. Also, the overall experiments are performed with a highly limited set heterogeneous smartphones, in a one-room-environment that is heavily controlled by the authors. In contrast, our PortLoc framework is a mobile friendly computationally inexpensive approach that is tested over a wide range of environments and heterogeneous mobile devices under realistic settings.

3 Analyses of Heterogeneous Fingerprints

We first present an analysis of the impact of smartphone heterogeneity on a conventional indoor localization technique: Euclidean-based KNN.

To capture the impact of device heterogeneity we observe the performance of the KNN technique to localize six users with six distinct devices (Figure 1(b)) on five benchmark paths (Figure 1(a)). Figure 2 shows the localization accuracy across all smartphones and paths, for four scenarios where the KNN model was trained on four different smartphones. The most interesting observation is that the best results are achieved when the device under test is identical in the (offline) training and (online) testing phases. For example, the average localization accuracy of KNN remains stable (< 2meters) when trained with OP3 on all paths (figure 2(d)). But this trend does not hold when the training device is not the same as the testing device. For example, training on the BLU smartphone leads to severe deterioration in accuracy in the Engr_Lab path when testing with the MOTO, SS7, and OP3 smartphones (figure 2(a)). For the Engr_Lab path in figure 2(c), we observe that the average error can be 8x between the best-case scenario (LG – LG), and worst-case scenario (LG – OP3). This suggests that a non-portable fingerprinting-based localization

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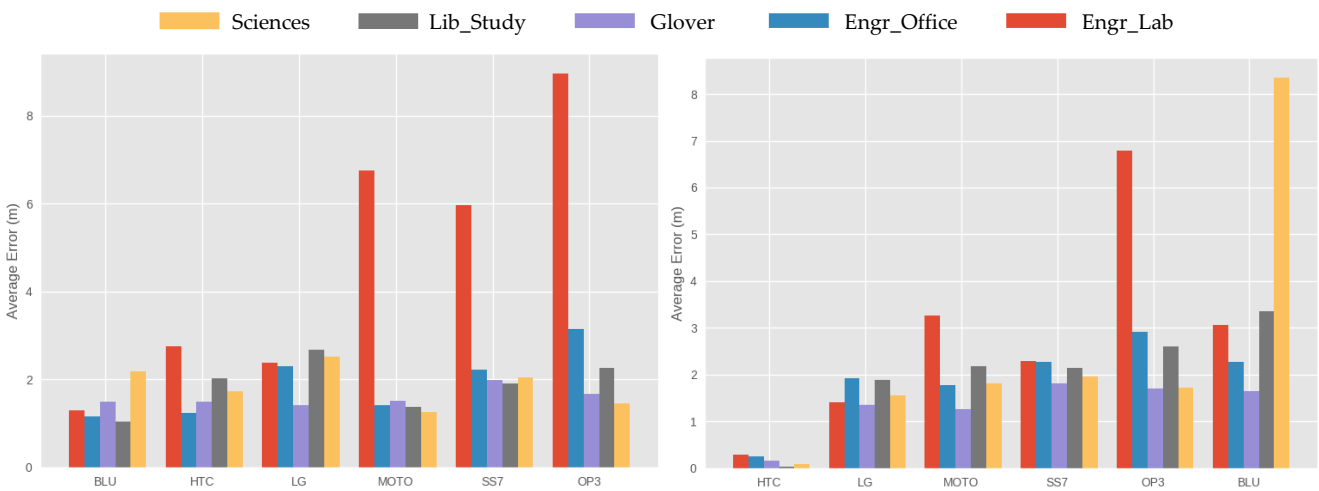
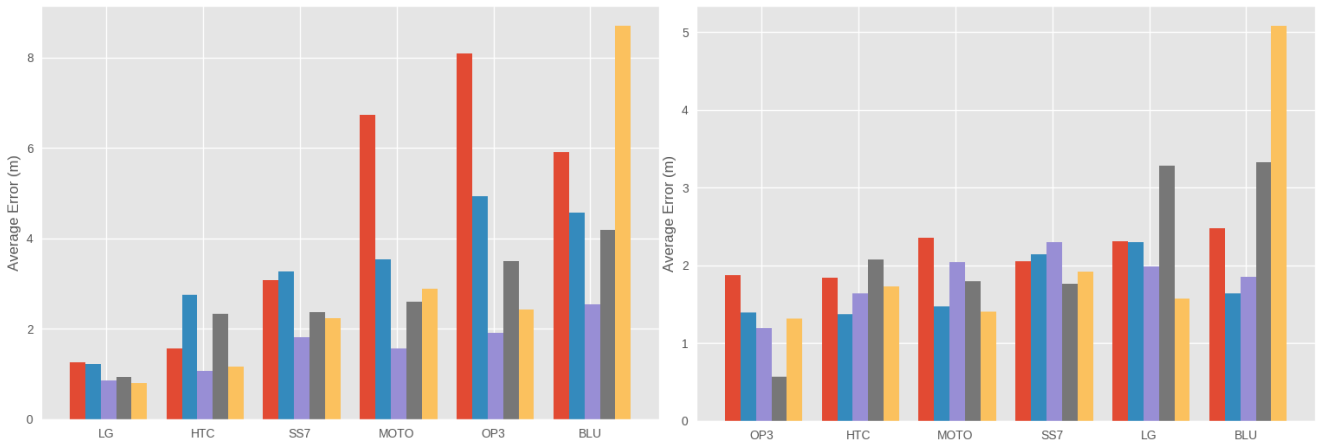


(a) Trained with BLU

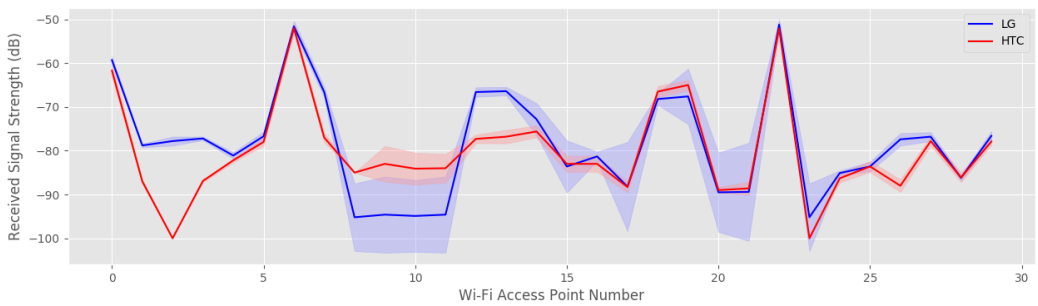
(b) Trained with HTC



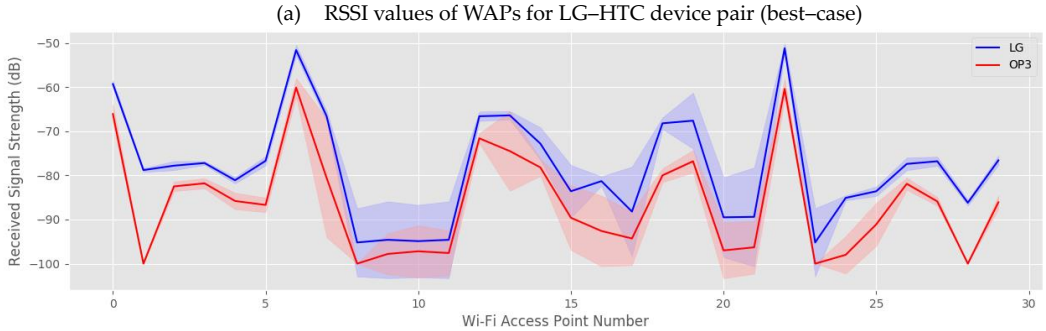
(c) Trained with LG

(d) Trained with OP3

Figure 2. Average Error for various benchmark paths using KNN algorithm



(a) RSSI values of WAPs for LG–HTC device pair (best–case)



(b) RSSI values of WAPs for LG–OP3 device pair (worst–case)

Figure 3. Average RSSI values of each WAP for training and testing pairs. Shaded regions represent the standard deviation of RSSI.

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framework may be extremely unreliable and unpredictable. However, the degradation due to device heterogeneity is not always observable, and KNN may be able to deliver acceptable results in some cases. Examples of such instances are in figure 2(b) for the Glover, Engr_Lab and Engr_Office paths. From the results in figure 2, we set the acceptable limit on average error to two meters and focus only on cases where the average error from KNN is beyond the acceptable error limit.

To better comprehend the cause of degradation in performance due to heterogeneity, we conduct another experiment. As KNN only takes into consideration the raw RSSI strength values of APs, we compare the best performing heterogeneous training-testing pair (LG–HTC) to the worst performing pair (LG–OP3) in terms of observed RSSI as seen on the Engr_Lab path in figure 2(c). For this experiment, we collected 100 RSSI fingerprints each using the LG, HTC, and OP3 smartphones at the same location on the Engr_Lab path.

The RSSI values for the best and the worst performing training-testing device pairs are presented in figure 3(a) and figure 3(b), respectively. The solid lines represent the mean values, whereas the shaded regions represent the standard deviations of RSSI values. From figure 3(a), there is a significant overlap in the RSSI values for the LG and HTC devices. This translates to a shorter Euclidian distance and therefore, produces good results using KNN. On the other hand, in figure 3(b) we observe only slight overlap in the RSSI fingerprints. This gap in overlap leads to the deterioration of localization accuracy for the LG–OP3 device pair.

Another observation that can be made from figure 3 is that the individual RSSI values of both fingerprints grow and drop at the same WAP. Therefore, a metric that captures this pattern of similarity for the two fingerprints should deliver better accuracy for our purposes. This serves as the core motivation for our proposed PortLoc framework, discussed next.

4 PortLoc Framework

In this section, we first discuss the fingerprinting and fingerprint management process required by PortLoc (sections 4.1-4.2). Then we present two variants of PortLoc based on two pattern matching metrics to enable heterogeneity-resilient indoor localization (sections 4.3).

4.1 Wi-Fi Fingerprinting

We utilize both the 2.4 GHz and 5 GHz Wi-Fi frequencies to capture the RSSI of a WAP along with its Media Access Control (MAC) address and the location (x-y coordinate) at which the sample was taken. The MAC address allows us to uniquely identify a WAP. The RSSI values for WAPs visible at each location are stored in a tabular form with the MAC addresses and the location as table headers, such that each row vector of RSSI values represents a fingerprint for the location in that row. Fingerprints are collected along an indoor path on a smartphone, by the user. This is a time-consuming labor-intensive manual step that is essential for any fingerprinting technique. Therefore, unlike some previous works [6], we collect a small number of samples per location (section 5.1.1). It is important to note that the deliverable accuracy from any fingerprinting-based localization approach is directly correlated to the granularity of sampling along a path. We chose to sample at 1-meter intervals along paths, to achieve a sufficient accuracy of a few meters.

4.2 Fingerprint Database Pre-processing

The captured fingerprints can be easily polluted by the temporarily visible Wi-Fi hotspots or third party owned Wi-Fi APs. Utilizing such RSSI values in our fingerprints can significantly reduce the overall reliability and security of our localization framework. Therefore, we only capture and maintain RSSI values for trusted MAC addresses that are found to be reliable WAP sources. Further analysis of data revealed that WAPs with very low RSSI values (< -90dB) were highly unstable and made it difficult to maintain the shape of the RSSI fingerprint. This led us to filter out all RSSI values that are lower than -90dB. These preprocessing steps improve the overall stability of PortLoc.

4.3 RSSI Data-aware Correlation Metrics

To predict the users' location in the online phase of PortLoc, we compute the similarity metrics discussed below, for the fingerprint of the unknown location and the database of known locations. The weighted sum of the locations in the fingerprinting database that produce the greatest value is the new predicted location. The number of similar locations taken into consideration is set to be the square-root of the fingerprinted samples per location taken in the offline phase.

Spearman's Correlation Coefficient (SPRMN)

In figure 3, we observed that individual RSSI values for different smartphones may be further apart, but the RSSI values rise-and-fall together. When two or more variables increase (or decrease) in the same direction, but not always at the same rate, they are known as monotonically dependent variables. SPRMN is a non-parametric test of the monotonic relationship between two variables. SPRMN for a given sample is represented by r_s and by design is constrained as follows:

$$-1 < r_s < 1$$

If the increase in one variable is followed by a decrease in the other variable, this is called an inverse monotonic relationship and is represented by a negative value. A positive value suggest that the variables increase and decrease together. The magnitude of r_s represents the strength of the positive or negative correlation between the two variables.

Zero Normalized Cross-Correlation (ZNCC)

ZNCC is a popular metric in the field of signal processing, single particle analysis, and image matching. It is a measure of similarity between two time-series as a function of displacement. Unlike Spearman's correlation, ZNCC is not bounded within a range, instead it is purely based on the magnitude of the time-series. The higher the magnitude, the stronger the match between the two time-series, for the selected time displacement. For our purposes, we assume each fingerprint to be a time-series and calculate the value of ZNCC for zero displacement.

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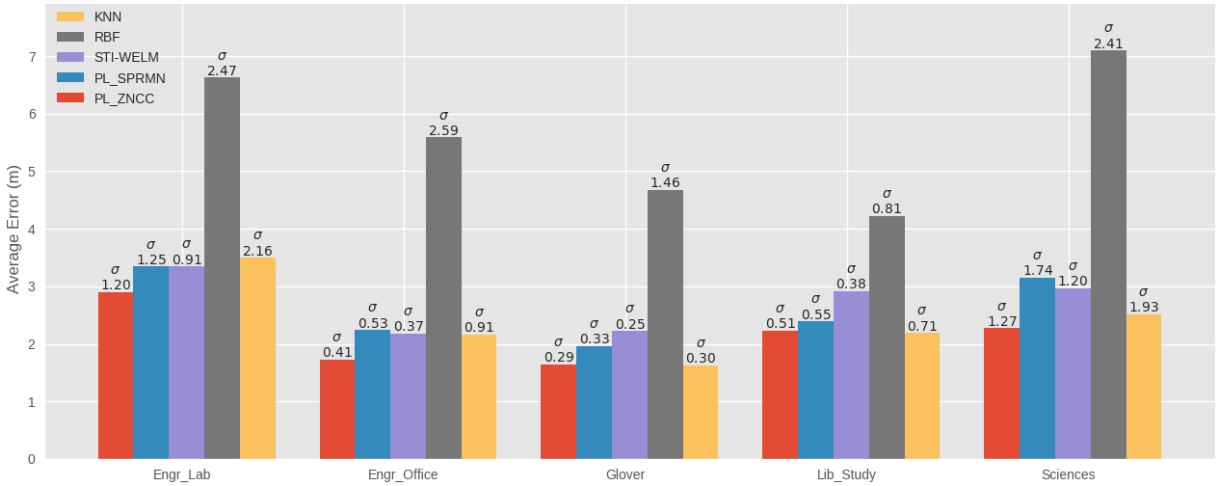

Fig. 4. Average error and standard deviation (σ) for indoor benchmark paths and localization frameworks

5 Experiments

5.1 Experimental Setup

5.1.1 Heterogeneous Devices and Fingerprinting

To investigate the impact of device heterogeneity, we employed 6 different smartphones (Figure 1(b)). Note that three of the devices have the same chipset. This allows us to explore the impact of device heterogeneity based on chipsets and vendors. We created an Android application that recorded the x-y coordinate from the user and included a scan button. Once the scan button was pressed, 10 consecutive Wi-Fi scans were conducted with an interval of 1 second. The RSSI value for each WAP and its MAC address was recorded in an SQLite database, and then processed as described in section 4.1.

5.1.2 Indoor Paths for Localization Benchmarking

We compared the accuracy and stability of PortLoc and frameworks from prior work on five indoor paths in different buildings on our campus. (Figure 1(a); each fingerprinted location is denoted by a blue dot). The path lengths varied between 60 to 90 meters.

Each path was selected due to its salient features that may impact indoor localization. The Glover building is one of the oldest buildings on campus and constructed from wood and concrete. This path is surrounded by a combination of labs that hold heavy metallic equipment as well as large classrooms with open areas. A total of 78 unique WAPs are visible on this path. The Behavioral Sciences (Sciences) and Library (Lib_Study) are relatively new buildings on campus that have a mix of metal and wooden structures with open study areas and bookshelves. We observed 112 and 218 unique WAPs on the Sciences and Lib_Study paths, respectively. The Engr_Office path is on the second floor of the engineering building that is surrounded by small offices and covered by 156 WAPs overall. The Engr_Lab path is in the engineering basement and is surrounded by labs consisting a sizable amount of electronic and mechanical equipment with about 125 visible WAPs. Both of these paths have large quantities of metal and electronics that lead to noisy Wi-Fi fingerprints and can hinder indoor localization efforts.

5.1.3 Comparison with Prior Work

We selected three prior works to compare against PortLoc. The first work (LearnLoc/KNN [3]) is a non-parametric approach based on the idea that similar data when observed as points in a multi-dimensional space would be clustered together. The second work (Rank Based Fingerprinting (RBF) [12]) claims that the rank of WAPs in a vector of ranked WAPs based on RSSI values remains stable across heterogeneous smartphones. Each vector of ranked WAPs represents a point in a Euclidian space, and these points for a given location on a floor map would be very close to each other. The third work combines Procrustes analysis and Weighted Extreme Learning Machines (WELM) [6] to predict the location of a user. Procrustes analysis allows the technique to scale and superimpose the RSSI fingerprints of heterogeneous devices and denote the strength of this superimposition as the Signal Tendency Index (STI). The STI metric is used to transform the original RSSI fingerprints, and then later used to train a WELM model in the online phase with the help of cloud servers.

5.2 Experimental Results

5.2.1 Accuracy Comparison for Benchmark Paths

Figure 4 shows the localization error across indoor benchmark paths for the two variants of PortLoc (PL_SPRMN, PL_ZNCC) and the prior works (KNN, RBF, STI-WELM).

The first notable observation from figure 4, is that the RBF technique performs the worst on all paths. The baseline non-heterogeneity aware technique, KNN, significantly outperforms RBF on all benchmark paths. KNN also performs better than STI-WELM and PL_SPRMN in most cases. PL_ZNCC delivers superior accuracy as compared to prior works RBF and STI-WELM. On the Glover path, where we observed the least impact of smartphone heterogeneity, PL_ZNCC closely tracks KNN performance.

Unfortunately, figure 4 does not compare the performance of localization frameworks on individual devices, and thus misrepresents the stability of KNN and other techniques across paths.

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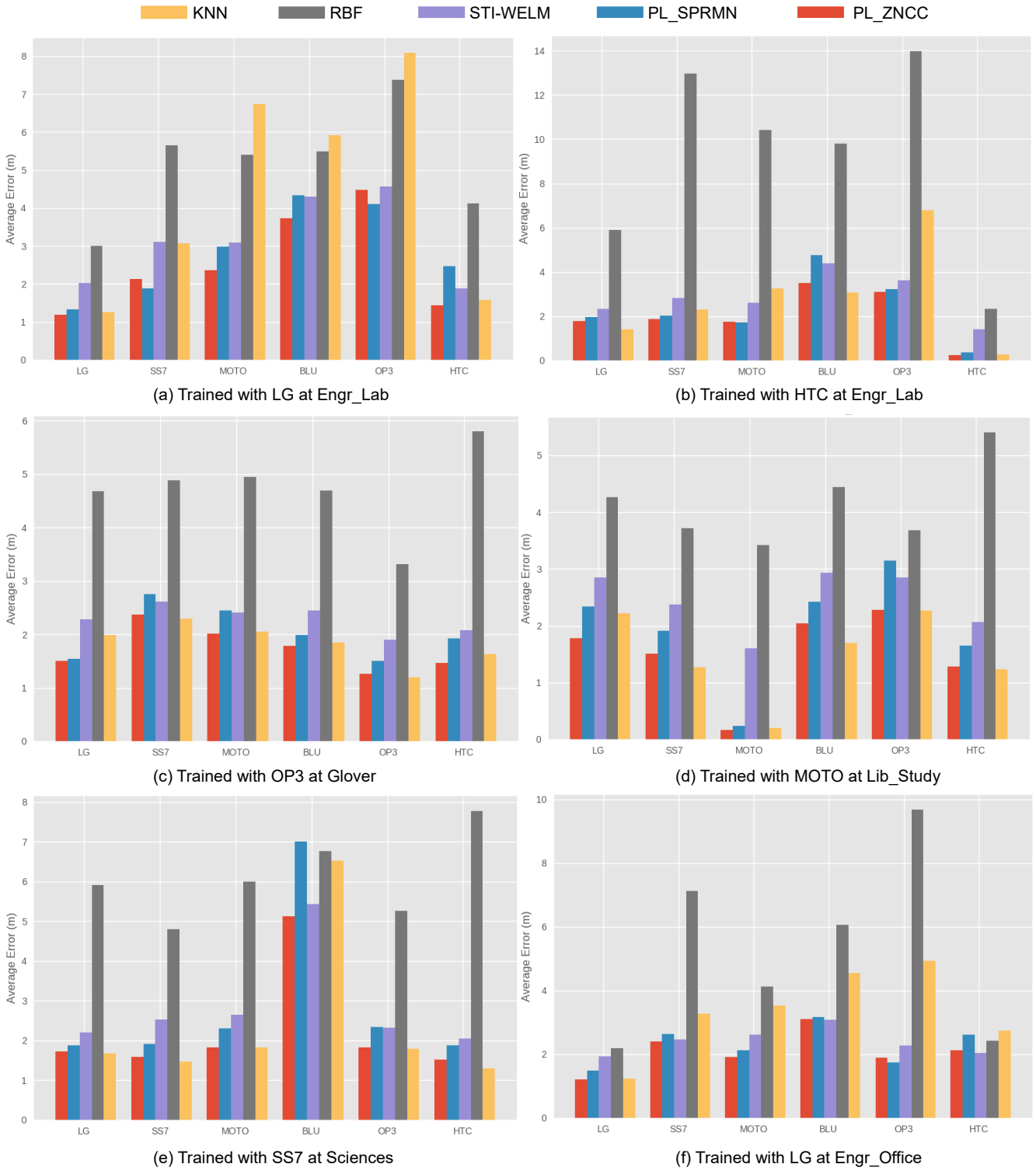

Fig. 5. Average Error for various techniques for benchmark paths and training devices

5.2.2 Detailed Performance of Localization Techniques

Figure 5 shows individual plots that represent the contrast in the localization experiences of six users carrying smartphones from distinct vendors. The paths along with the training phase device combinations were chosen based on the analysis of the plots in figure 2. We chose to focus on cases that demonstrated significant deterioration in localization error (above 2 meters) for the non-heterogeneity aware baseline KNN technique.

From figure 5(a), HTC is the most stable device for KNN, i.e., is least affected by heterogeneity. In all other situations, localization is heavily impacted by heterogeneity. Figure 5(a) is also the only case where RBF performs better than KNN. This suggests that the observed order of strengths of RSSI values for WAPs remain relatively stable in the case of figure 5(a) as compared to all other plots in figure 5. Another notable aspect is that this improvement is not maintained when the training device is replaced by HTC in figure 5(b) for the same benchmark path. Overall,

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in figures 5(a) and (b), PortLoc variants outperform RBF and STI-WELM whenever the localization error from the baseline KNN technique is greater than two meters.

We observe that the RBF technique performs the worst when there is a significant amount of metal in the surrounding environment. This is the case for the engineering building paths (Engr_Lab and Engr_Office) and the path in the Glover building. The perturbations in the Wi-Fi AP RSSI values due to the metallic surroundings cause the ranks of the AP RSSI values to become highly unstable.

From figure 5, we also observe that the proposed PortLoc variants outperform STI-WELM in most training-testing device pairs. We believe PortLoc is able to deliver superior performance as it is a purely pattern matching based approach. On the other hand, the STI-WELM framework identifies the closest sampled locations from the offline phase using the shape matching based STI metric. The fingerprints of these closest locations are then used to train a WELM based neural network in the online phase itself. This neural network model is not specially designed for pattern matching, and sacrifices predictability of localization error for faster training time in the online phase.

It is interesting to note that under certain situations PL_SPRMN performs worse than STI-WELM, such as on the Glover (figure 5 (c)), Lib_Study (figure 5(d)) and Sciences (figure 5 (e)). But in all of these cases PL_ZNCC outperforms PL_SPRMN and STI-WELM. In contrast, the PL_SPRMN technique seems to perform slightly better than PL_ZNCC in some training-testing combinations for the engineering building paths (figures 5 (a), (b), (f)). These observations suggest that there is no clear and obvious winner among the two variants of PortLoc. We also note that for most paths in figure 5, PortLoc variants, especially PL_ZNCC, perform closest to KNN in the case of non-significant heterogeneity-based accuracy loss. Our work thus strongly motivates the intelligent combination of computationally inexpensive pattern matching based techniques to enhance the effectiveness of device heterogeneity aware localization frameworks that utilize fingerprinting.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we have established that the proposed PortLoc framework is a computationally inexpensive solution to the device heterogeneity problem in the fingerprinting-based indoor localization domain. The advantage of establishing portable machine learning models that can be easily ported across devices with minimal loss in localization accuracy is a crucial step towards the actuation of fingerprinting-based localization frameworks in the real world. Our future work will explore filtering strategies to further enhance the accuracy of PortLoc.

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