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HMF: Heatmap and WiFi Fingerprint-based Indoor Localization with Building Layout Consideration

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***Abstract*—In recent years, WiFi fingerprint-based localization has received much attention due to its deployment practicability. Although existing works show WiFi fingerprinting can achieve good localization accuracy, the experiments were conducted under their own testbeds within a small area and a short period. In this work, we investigate the impact of different indoor environmental factors, such as temporal and spatial similarity, on the performance of WiFi fingerprinting. We find that, WiFi fingerprinting is highly environment-sensitive. In an open space, it is quite challenging to find spatially varying but temporally stable signatures for adjacent reference locations. To address this issue, we propose a heatmap-based WiFi fingerprinting (called HMF) by utilizing layout construction as an additional input to improve WiFi fingerprint localization in open space environment. Our experimental results show, HMF can improve existing WiFi fingerprinting schemes like Radar and Horus by 28% and 80% in moderately open space, e.g., a wide corridor.**

***Keywords*-indoor localization; WiFi fingerprint; open space; heatmap; building layout**

I. Introduction

While GPS (Global Positioning System) is the most common positioning system, it cannot work well in indoor environment. The increasing need for location-based services (LBS), such as navigation, tracking, and mobile advertising, has motivated significant research effort in the area of indoor localization. Various indoor localization techniques have been developed, including proximity-based [1], range-based [2], fingerprint-based [3], and device-free passive localization [4].

We are witnessing the increased deployments of 802.11 WiFi access points (APs) and WiFi infrastructure has become essential condition for indoor environment, such as office, restaurant and home. WiFi-fingerprinting based localization has attracted a lot of interest over the last decade, since it makes the design of an easily deployable infrastructure-less low-cost localization system possible. A WiFi-fingerprinting system works in two phases: an offline training phase and an online localization phase. The first phase collects fingerprints (radio signal strength (RSS) measurements of WiFi APs) from different pre-known locations and stores them to a database as the training set. The second phase infers the location based on the observed RSS measurements, through finding the closest match in the database.

Several existing research demonstrated that WiFi fingerprint localization can achieve varying degree of average localization accuracy between (0m, 10m). For example, Horus [5] demonstrated that it can achieve sub-meter accuracy. EZ [6] demonstrated median localization error of 2m and 7m.

Now, from customers point of view, we must ask ourself following question. Can we expect similar localization performance if we deploy one of these existing methods in our indoor environment? The answer to this question is probably NO, since their performances were tested under their own testbeds. Since Horus is a popular benchmark, Zee [7] and EZ [6] show that accuracy of Horus was 3m and 4m under their testbeds, respectively, rather than the sub-meter accuracy in Horus [5]. This evidence indicates that the performance of WiFi-fingerprinting depends on the indoor environment at which it is deployed.

In this paper, we present the empirical evaluation work that investigates the impact of different indoor environmental factors, such as temporal and spatial similarity, towards the performance of WiFi-fingerprinting. Our evaluation is performed using Horus. We select the Horus since it is a good benchmark system where its performance solely relies on RSSIs and its associated APs, while other WiFi fingerprint localizations utilize additional inputs such as building layout or inertial sensor information.

Our contributions are listed as following:

- To the best of our knowledge, this is first work analyzing the performance of WiFi fingerprint radio map based on a new metrice γ which measures the spaciousness of the indoor environment in which WiFi fingerprinting is deployed.
- We show temporal similarity affects the reliability of WiFi fingerprinting over time and its effect is stronger for WiFi fingerprinting requiring high localization accuracy.
- We propose heatmap-based WiFi fingerprinting (HMF) by utilizing building layout as an additional input. Experimental results demonstrate that our method can

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improve existing Radar and Horus by an average of 28% and 80% in moderately open space in wide corridor.

The outline of the paper is as follows. Section II surveys the related work. Section III introduces the environment factors that are studied in this paper. Section IV presents impact of environmental factors on WiFi fingerprinting accuracy. Section V provides our proposed heatmap design in detail. Section VI shows the experimental results. Finally, conclusions are drawn in Section VII.

II. Related Work

In this section, we briefly review previous work on fingerprinting techniques, especially WiFi fingerprinting, for indoor localization.

Several fingerprinting techniques have been developed for indoor localization, such as utilizing the in-building communication infrastructures (WiFi[5], RFID [8] and Cellular [9]), ambient light and color [10], magnetic field [11], inertial sensor landmark [12] and visual features [13], to identify a specified location in an indoor space. The major challenging issue of fingerprinting techniques is to find spatially varying but temporally stable signatures for different locations.

With the increased deployments of ubiquitous 802.11 WiFi access points (APs), WiFi fingerprint-based indoor localization is considered as the most promising localization method due to its deployment practicability. The idea is to utilize the received WiFi signal strength (RSS) to estimate the location of a user. WiFi fingerprinting has two stages: calibration (offline training phase) and localization (online phase). It first constructs WiFi signal fingerprints database (also called radio map) for individual locations, which usually consists of WiFi signal strengths along with ground truth information. During the online phase, the observed WiFi signal measurements associated with an unknown position is compared and matched with the most likely fingerprint in the database. Horus [5] and [14] use a Gaussian distribution to statistically model WiFi signal strength observations to estimate the user location. SurroundSense [10] discovers semantically meaningful places based on ambience features including WiFi, sound, light and color, etc.

Traditionally, WiFi fingerprint databases are built by dedicated operators who gather received signal strengths using WiFi-enabled devices. However, the fingerprint database construction is cumbersome and incurs a relatively high cost, i.e., the need for signal measurements from known locations still remains a bottleneck [15]. More recently, several studies have attempted to reduce the effort needed for the database construction. ZEE [7] presents a system that introduces the crowdsourcing (participatory) based training data collection and thus makes the calibration effortless. However, the participatory approach also introduces new challenges, e.g., the device diversity issue. FreeLoc [16] presents an efficient localization method addressing the major technical issues posed in crowdsourcing based systems.

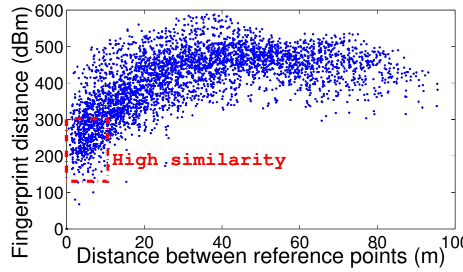


Figure 1. Correlation between reference points in wide and long corridor ($10m \times 100m$). There are total of 89 reference points deployed on the corridor and in the meeting rooms.

Although WiFi fingerprinting has attracted extensive research efforts in recent years, it is not a solved problem. In this work, we empirically reveal a new challenging issue that existing proposed WiFi fingerprinting techniques have not taken into account. We find that, in open environment such as corridors or big conference rooms without many barriers, adjacent locations always generate similar WiFi signatures, which may hinder the proper functioning of WiFi fingerprinting. To address this issue, we also propose a simple yet effective method to improve WiFi fingerprint localization in open space environment and evaluate its performance in our testbed.

III. Existence of Environmental Factors

When RF signals from different APs propagate through indoor environment with many rooms and barriers, they generate unique signatures at different locations. In such environment, WiFi fingerprint based indoor localization provides accurate location estimation for the mobile users since reference points in the radio map built from collecting these WiFi fingerprints have low similarity among them.

However, in an open space like a wide corridor or a big conference room, the accuracy of radio map could deteriorates since signals measured among nearby reference points have high similarity. Consequently, the localization accuracy of fingerprint reduces. Next section experimentally proof that fingerprints from some reference points in open area have high similarity and they change even after a short period of time.

A. Spatial Similarity

In Figure 1, we show similarity between two different fingerprint measured from two different locations. Figure 1 demonstrates that if geographical distance between two reference points are greater than 20m apart, the fingerprint measurement taken at those two locations are generally different and distinguishable. However, Figure 1 also suggests that fingerprint measurements from any two nearby locations (< 10m) are similar and indistinguishable. In order to understand the fingerprint characteristics in small-scale,

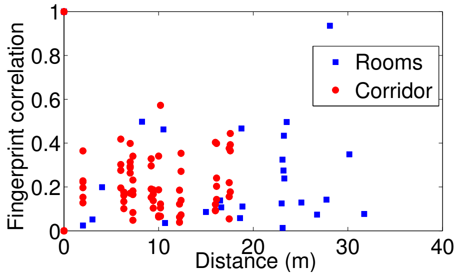


Figure 2. Correlation between nearby reference points

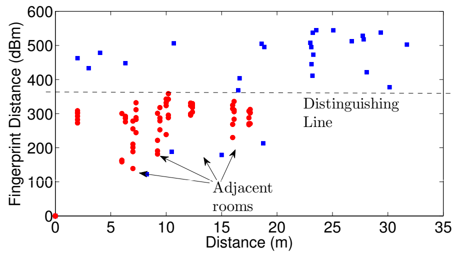


Figure 3. Fingerprint distance between nearby reference points

we conducted a case study. We divide the reference points into two different sets based on whether it is located in the small room (closed space) or on the corridor (open space). Then, we measured the fingerprint distance between every pair of rooms and every pair of reference points on the corridor (outside the rooms).

In Figure 2 and Figure 3, we show similarity between fingerprints for this small-scale case study. In Figure 2, we attempt to measure the similarity between fingerprint using correlation coefficients. It shows that correlation between reference points varies randomly between [0, 0.4]. However, it is indistinguishable between a set of reference points in the corridor and rooms. We also have observed that fingerprint distance (euclidean distance between fingerprint) metric provides the best distinguishable clustering within the reference points between rooms and corridor. It is clear from Figure 3 that fingerprint distance between rooms are higher than the reference points on corridor even if their geographical distance is same.

B. *Temporal Similarity*

WiFi fingerprint changes dynamically overtime since indoor environment itself is not static. It has been known that reliability of radio map reduces after long duration of time (in a scale of days). However, it is often assumed in the literature that WiFi fingerprints do not change over short period of time. In order to investigate short-term variation of fingerprint measurement, we conducted experiments at 20 different locations and scanned the fingerprint for 1000s while users were stationary.

From this experiment, we have observed that WiFi fingerprint changes over short period of time as well. Figure 4 shows average fingerprint distance changing over a period of

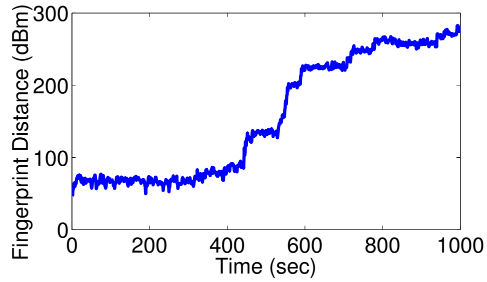


Figure 4. Variation of average fingerprint distance over time

1000s. Notice that fingerprint stays stable for first 400s and then it begin to deviate away rather quickly over next 600s. This small deviation is enough for fingerprint to incorrectly localize users to any nearby reference points although they are actually stationary.

IV. Evaluation

In this section, we first evaluate the impact of spatial similarity of indoor environment by implementing Horus system at four regions with different level of line of sight between every pair of reference points. Next, we evaluate the impact of temporal similarity by testing Horus at different time scale.

A. *Impact of Spatial Similarity*

In order to generalize the impact of spatial similarity, we define γ, which is average euclidean distance between every pair of reference points in the WiFi-fingerprint radio map, if a pair of reference points has a line-of-sight and their distance is less than maximum transmission range of AP. The metric γ attempts to measure the spaciousness of an area relative to WiFi-fingerprinting. For example, the value of γ would be almost zero for an office building with many small rooms if one reference point is located in each room. In contrast to office building, the γ would be reasonably big for an open area like a large concert hall without too many reference points inside the hall.

After defining the γ, we have conducted WiFi-fingerprinting experiments at four distinctive areas: office building, wide corridor, lecture theatres, complete complete open space. Office building is where lots of rooms are connected by some narrow pathways. An example of such area is shown in the figure 5. For office building testbed, we deployed one reference point in each room and few of them on the corridor as shown in the figure 5. Figure 6 shows the layouts of lecture theatres, wide corridor, and complete open space. Wide corridor is WiFi fingerprint testbed where most of reference points are deployed on straight wide corridor (average width is 5m) with some rooms on each side of the corridor. Lecture theatres is an area where class rooms of size greater than $20m^2$ are clustered together. In this testbed, one or two reference points are deployed in each lecture rooms and rest of the reference points are outside the lecture rooms. complete open space is a spacious complete open space in indoor location where one side is connected to a small garden and total area is greater than $200m^2$. The reference points are uniformly deployed in the complete open space.

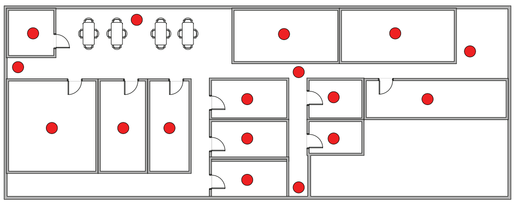


Figure 5. Floor layout of office building and reference points in WiFi fingerprint radio map are marked on the layout.

For the office building testbed, no pair of reference points has the line-of-sight view from each other and therefore $\gamma = 0$ in this case. The γ for other three testbeds are shown in the Table I.

Area Type	Office building	Lecture theatres	Wide corridor	Complete Open space
γ	0.0	6.8	7.3	9.7

Table I
THIS TABLE SHOWS γS FOR DIFFERENT AREAS

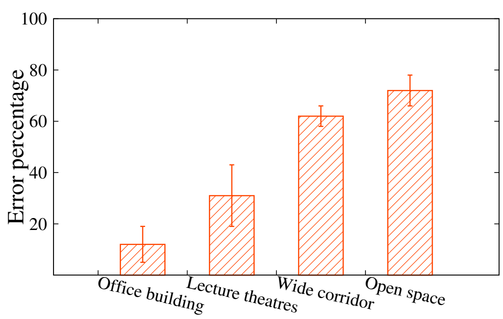


Figure 7. WiFi fingerprinting accuracy of different testbeds

It is now well known that user mobility, body absorbing signal, and location of phones can cause small variation in the fingerprint measurement. In this experiment, the accuracy of WiFi fingerprinting is measured based on the error probability of user's current location being not equal to the estimated reference point. In order to obtain consistent results, we remove the effect of user mobility by applying WiFi fingerprinting whenever the user is standing next to the reference points. Each of these four testbeds has different spatial similarities.

Figure 7 shows WiFi fingerprint accuracy at four indoor areas with different γ levels. The office building with $\gamma = 0$ has the lowest localization error of 18%. Whereas the highest localization error of 73% is the complete open space in which every pair of reference points is in line-of-sight. Also the results in Figure 7 indicates that there exists a proportional relationship between WiFi fingerprinting localization error probability and the γ. Therefore, one can use this result to predict whether WiFi fingerprinting would be a sufficient localization solution for their indoor environment. This result in Figure 7 also demonstrates that WiFi fingerprinting would be an ideal solution for logical localization at a room level but not sufficient for physical localization requires the accuracy of less than 10m in an complete open space where γ is high.

B. Impact of Temporal Similarity

The indoor environment changes dynamically over time. Due to this dynamic changes, reliability of radio map of WiFi fingerprinting also expected deteriorates over time. In order to understand how the accuracy of WiFi fingerprinting changes overtime, we have collected the 1000 fingerprints everyday at every reference points over a period of one month.

Figure 8 represents the change of probability of accurately localizing users below 2m and 9m with respect to time (in the scales of days). Figure 8 shows that the probability of maintaining the localization accuracy below 2m exponentially decreases while the probability of localizing users below 9m remains reasonably stable over time. This indicates the reliability of radio map of WiFi fingerprinting is low if application requires high localization accuracy. On the other hand, WiFi fingerprinting can be used for the applications which can tolerate large localization error (e.g. > 9m).

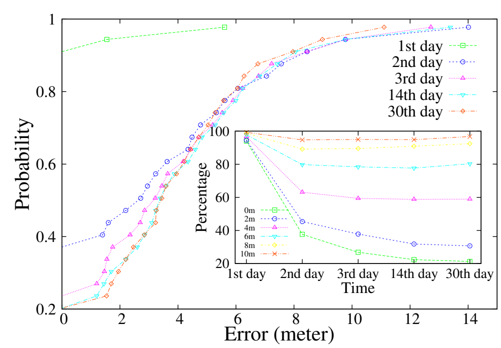


Figure 8. CDFs of WiFi fingerprinting accuracy over time

This result of short-term variation of fingerprint measurements again reinforces our conclusion from spatial similarity that the WiFi fingerprint alone is not sufficient for physical localization with high accuracy (< 2m) in the complete open space.

V. HEATMAP-BASED FINGERPRINTING

We have empirically demonstrated in Section IV that expected performance of WiFi fingerprinting strongly depends on the spatial and temporal similarity between any near by reference points. This suggests that additional input is necessary in order to guarantee high accuracy of WiFi fingerprinting method for the indoor environment with high γ.

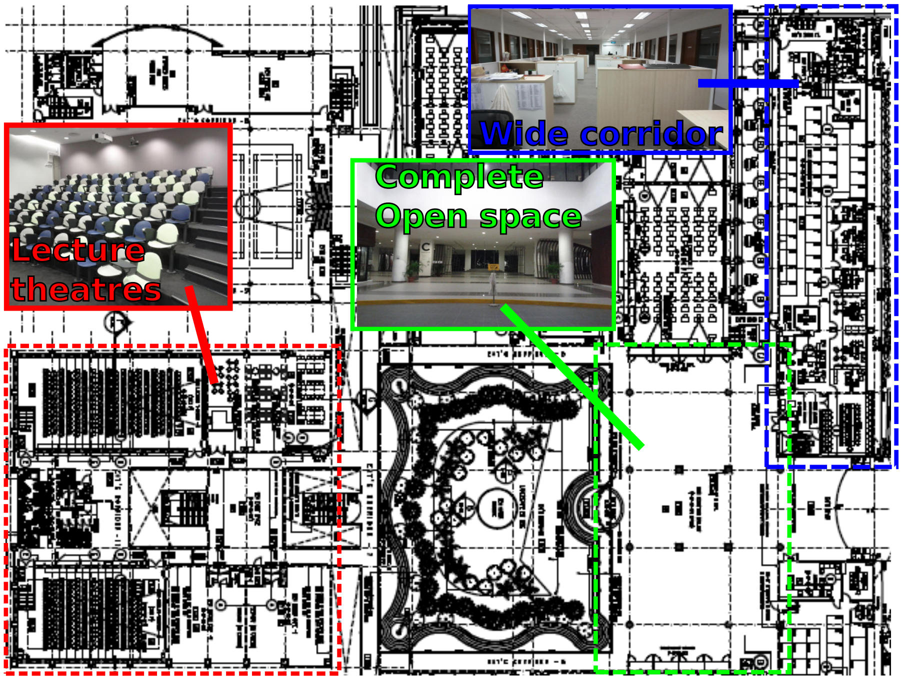
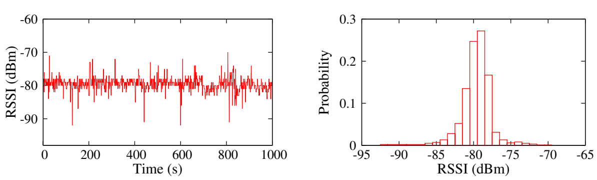


Figure 6. Floor layout and pictures from the WiFi fingerprint testbeds of lecture theatres (red box), wide corridor (blue box), and complete open space (green box).

Here, we propose heatmap-based fingerprinting a quick and effective solution to improve RSS distribution based WiFi fingerprinting method by utilizing building layout as an additional input.

A. Motivation of Heatmap design



(a) RSS varies over time

(b) Normalized RSS histogram from an AP

Figure 9. RSS characteristics of AP

Beside the spatial-temporal similarity, there are many factors in indoor environment which can influence the RSS of an AP, such as walking human, door opening or closing, multi-path phenomenon, etc. Figure 9(a) and Figure 9(b) depict the characteristics of RSS variation from AP. The RSSs are collected from smart phone while the holder is stationary on the wide corridor. In Figure 9(a), we can see a typical jitters of the RSS variation which shows that the RSS was not stable even at the same location. So, most of the time, we can use a normalized histogram which contains the variation characteristic of the RSS samples to encapsulate the unique feature of one AP at a specific location. Figure 9(b) shows the normalized histogram of the RSS samples from Figure 9(a).

RSS probability distribution based WiFi fingerprint localization has been performed in some previous works [5], [17]. Given the observed RSS vector $\bar{S} = (s_1, ..., s_k)$, while s_k is the measured RSS of number k AP. The predicted location l^* was computed in Equation 1.

$$l^* = \underset{l}{\operatorname{argmax}}\, P[l|\bar{S}] = \underset{l}{\operatorname{argmax}} \frac{P[\bar{S}|l] * P[l]}{P(\bar{S})} \tag{1}$$

Both of these two works has two assumptions. Firstly, they assumed that all the potential locations are equally likely and considered the term $P(\bar{S})$ as a constant which is factored out from Equation 2. Secondly, they consider $P(\bar{S})$ remains stable for long duration of time which is also a constant. So actually the predicted location l^* was computed by Equation 2.

$$l^* = \underset{l}{\operatorname{argmax}}\, P[l|\bar{S}] = \underset{l}{\operatorname{argmax}} \prod_{i=1}^{k} P(s_i|l) \tag{2}$$

$P(s_i|l)$ is estimated from the histograms which contains the RSS distributions.

B. Heatmap-based WiFi Fingerprinting

The uniform distribution of user's location over the set of possible locations is a common assumption of WLAN localization systems [5]. However, if we know the distribution of user's location, that is, user has higher probability at a certain location or area, it can help to increase the localization accuracy. Many previous works, such as Horus[5], focus on maximizing $P[\bar{S}|l]$ to improve the performance of fingerprint-based localization and assume that $P(l)$, the probability of user's current location, is uniformly distributed over all reference points and $P(\bar{S})$ remains stable for long duration of time. But, in fact we provided the evidence in Section III that $P(l)$ is not uniformly distributed and changes over time. So, instead of set $P[l]$ and $P[\bar{S}]$ to a constant, we exploit the distribution of user's location $P(l)$ by heatmap, which is calculated by utilizing a period of history estimations. In section V-C, we show how the heatmap was built. Let $\mathbb{L}$ is the list of all the reference locations and l_i is i_{th} reference location in $\mathbb{L}$. The heatmap of time t can be described by $H_t = \{P[l_1], P[l_2], P[l_3], ..., P[l_{n-1}], P[l_n]\}$. H_t represents the distribution of user's potential location at time t. For our HMF, the estimated location l^* was calculated by Equation 3.

$$l^* = \operatorname*{argmax}_{l} \frac{P[\bar{S}|l] * P[l]}{\sum_{i=1}^{n} P[\bar{S}|l_i] * P[l_i]} \tag{3}$$

We introduce the influence of bounding the $P(l)$ by utilizing the idea of heat map and further improve the estimation of $P(l)$ by utilizing a short period history of user's location estimation. Consequently, we further improve the performance of fingerprint.

C. Fingerprint Heatmap Building

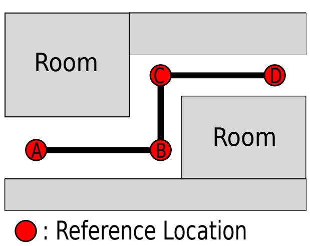


Figure 10. Connectivity graph for reference points

Fingerprint based localization based on the unique feature of different locations. But due to small scale variations, As shown in Section III, the estimated location is not stable and keep jumping. The instantaneous location estimation is not reliable. However, since the basic WiFi fingerprint localization has a reasonable accuracy, based on the observation of a certain period, we can roughly know which area or location has higher probability to be the ground truth location. Here, we present fingerprint heatmap which is a distribution of users potential locations. We use the connectivity between reference points and statistics from past estimated locations to build this heatmap. For example shown in Figure 10, two reference point A and B is connected since these two location is physically connected and there is no other reference points between them. reference point A and C is not directly connected since we must come close to reference point B before we can reach C. The probability of each reference point is assigned by adding a set of consecutive WiFi fingerprint estimation. For example, reference point A and B previously have heatmap value of 0.8 and 0.2, respectively. If WiFi fingerprint estimates $P(\bar{S}|B) = 0.6$ and $P(\bar{S}|D) = 0.4$ we update $P(B)$ by $P(\bar{S}|B)+0.2$ but ignore $P(\bar{S}|D)$ since D is not connected to B directly. The heatmap indicates that the current potential locations of user are B or D. The detail algorithm is shown in *heat map building* algorithm1. Since our heatmap are build based on the basic fingerprinting method, we assumed that we already have a WiFi fingerprint radio map $\mathbb{F}$ from which we can get $P[\bar{S}|l]$ of every reference points given WiFi fingerprint $\bar{S}$.

Algorithm 1: Heatmap building

Input: fingerprint map $\mathbb{F}$, reference location set $\mathbb{L}$, live WiFi fingerprint $\bar{S}_t$ at time t , heatmap sliding window w and δ for heatmap reduce.
Output: H_t which represent the heatmap of time t.
t=0;
$\forall l \in \mathbb{L}$, $P[l_i] = 1/size(\mathbb{L})$;
while $t <= t_{end}$ **do**
  given $\bar{S}_t$, compute vector $V_t = \{P[\bar{S}_t|l_i]\ , l_i \in \mathbb{L}\}$;
  if $(t > w)$ **then**
    $H_t = 0$;
    for $l_i \in \mathbb{L}$ **do**
      $P[l_i] = \frac{1}{w} \sum_{t=t-w}^{t} P[\bar{S}_t|l_i], \forall l \in \mathbb{L}$;
      $H_t[i] = P[l_i]$;
    for $l_i \in \mathbb{L}$ **do**
      if $H_t < \delta$ **then**
        $H_t = 0$;
    normalize H_t;
    return H_t;
  else
    save V_t to Queue Q;
  $t++$;

VI. HMF Evaluation

The heatmap compliments WiFi fingerprinting by bounding the $P(l)$ to a small subset of reference locations. In this section, we present the experimental result of HMF localization and compared it with Horus and Radar which are two well accepted WiFi fingerprint solutions in practice.

A. Experiment Setup

1) Testbed: We evaluate our HMF localization scheme under two different testbeds: wide corridor and open space. The floor layout of this two testbeds are shown in Figure 6. The dimension of the wide corridor testbed is 107×7 meters and there are totally 249 APs were detected in this test bed. Another one is the open space testbed and it's size is 36×24 meters. In this testbed, there are totally 110 APs. We have a total of 89 reference points in wide corridor testbed. The average distance between these reference points are 2.5m. On the average, each location is covered by 12 access points. For test bed 2, there are 77 reference locations and each location can detect about 15 APs.

2) Offline Data Collection: We use 10 Sony Acro S smart phones to collect the WiFi training set and the realtime experiment. WiFi training data used to build WiFi fingerprint radio map was collected over different time in the scale of days, weeks, and months. At each time, we collect WiFi training data of 1000 fingerprints continuously at each reference point.

3) Realtime Experiment: In order to evaluate the expected performance of HMF in practice, we walk through all the tags one by one. At each reference location, we rest for several seconds and then move ahead.

B. Experimental Results

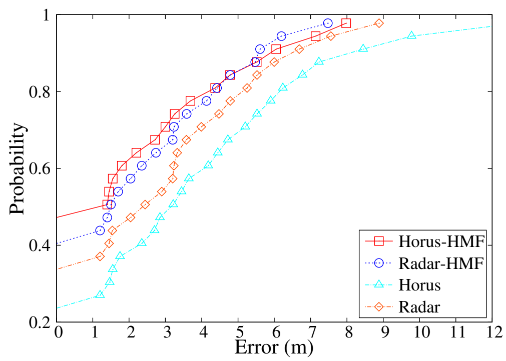


Figure 11. Performance of HMF compared to Horus and Radar in wide corridor testbed.

Figure 11 depicts the distribution of localization error seen by Radar and Horus at the wide corridor testbed. Our result shows Radar performs better than Horus over all localization error range. In the same figure, we show that utilizing heatmap improves average performance of normal Radar by 28% and 5% with probability of 0.8. Utilizing heatmap on Horus improves average performance of Horus by 80% and 11% with probability of 0.8. Our results show heatmap complement probabilistic design of Horus more than Radar which uses KNN for estimating the user's current location.

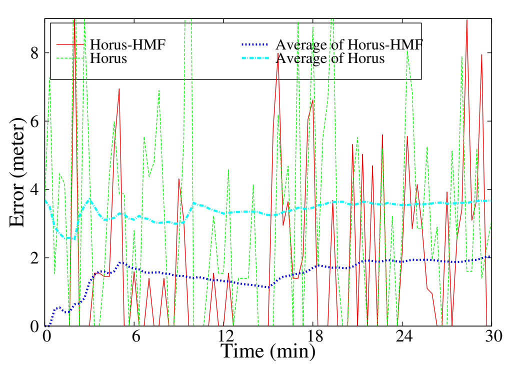


Figure 12. Performance of Horus and HMF Horus overtime in complete open space testbed

Figure 14 shows performance of Horus and heatmap-based Horus over time period of 30min. The result show heatmap can improve average performance of Horus by at least 45%. The instantaneous performance shows that heatmap-based Horus begins with zero localization error while regular Horus begins with 4m error. This is due to a inherited benefit of heatmap. If user start its walk from stationary heatmap can localize the user while he is standing still although user initial location is not known in the beginning. Whereas, regular Horus can not correctly estimate the user's initial location unless it is given. Our experiment result in Figure 13 show that resting time of 4s is enough to localize the user with below 2m accuracy.

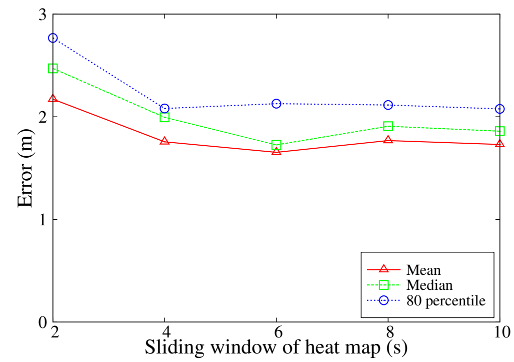


Figure 13. Performance dependence on amount of training data

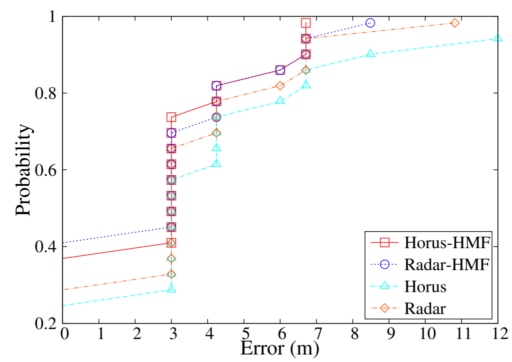


Figure 14. Performance of HMF compared to Horus and Radar in open space testbed.

Figure 11 depicts the distribution of localization error seen by Radar and Horus in the complete open space testbed. Our result shows Radar performs better than Horus over all localization error range. The CDF looks more like a step function. This is due to a fact that reference points are deployed uniformly in the complete open space testbed and the distance between every pair of any adjacent point is 3m. In the same figure, we show that utilizing heatmap improves average performance of normal Radar by 10% and 41% with probability of 0.8. Utilizing heatmap on Horus improves average performance of Horus by 33% and 41% with probability of 0.8.

Notice that the improvement is less significant in this testbed compared to wide corridor. This is due to heatmap being able to utilize some unique reference points which has very low spatial similarity with its nearby reference points in the wide corridor whereas there is almost no unique reference points in complete open space testbed.

C. impact of training data size

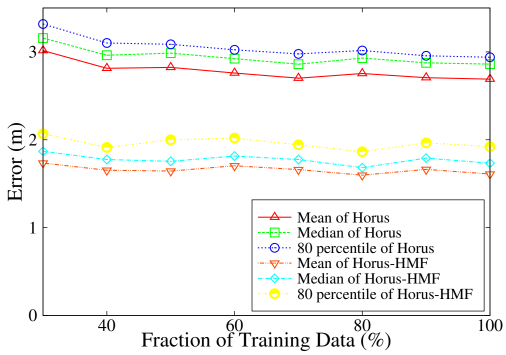


Figure 15. Performance dependence on amount of training data

We collected 1000 WiFi fingerprint at each reference points to build the database. Figure 15 shows the relation between training database size and localization accuracy. When training size of Horus increase from 300 WiFi fingerprint scanning to 1000 the average localization error of Horus improves by 9%. In contrast to regular Horus, heatmap-based Horus do not show clear improvement when training size increase. This means employing heatmap can reduce the dependency of WiFi fingerprinting to its training set size.

VII. CONCLUSION

In this work, we first identified the existence of spatial and temporal similarity which limits the performance of WiFi fingerprinting. Then, we have investigated the impacts of spatial and temporal similarity by conducting extensive experiments under 4 different testbeds in which their spatial similarities are different. Our initial result shows that this spatial similarity is high in case of large open space and consequently, WiFi fingerprint performance reduces in this environment. We also show temporal similarity can reduce the reliability of WiFi fingerprinting radio map to 40% only after one day if location accuracy of less than 2m is required. These two results demonstrate that WiFi fingerprinting alone is not sufficient and additional information must be presented as an additional input to WiFi fingerprinting to achieve higher localization accuracy in the open space.

Based on the empirical results, we proposed heatmap-based WiFi fingerprinting, fast and effective method improving WiFi fingerprinting by utilizing the information from the building layout. Our performance evaluation indicates that heatmap-based WiFi fingerprinting is effective and improves the localization accuracy by 40% for all four different testbeds compared to regular Horus and Radar. It also maintains its accuracy for longer duration of time.

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REFERENCES

[1] R. Want, A. Hopper, V. Falcão, and J. Gibbons, "The active badge location system," *ACM Trans. Inf. Syst.*, vol. 10, no. 1, pp. 91–102, Jan. 1992.

[2] K. Whitehouse and D. Culler, "A robustness analysis of multi-hop ranging-based localization approximations," in *Proc. IPSN '06*, 2006.

[3] D. H. Kim, Y. Kim, D. Estrin, and M. B. Srivastava, "Sensloc: sensing everyday places and paths using less energy," in *Proc. ACM SenSys '10*, 2010, pp. 43–56.

[4] M. Youssef, M. Mah, and A. Agrawala, "Challenges: device-free passive localization for wireless environments," in *Proc. ACM MobiCom '07*, 2007, pp. 222–229.

[5] M. Youssef and A. Agrawala, "The horus wlan location determination system," in *Proc. MobiSys '05*, 2005, pp. 205–218.

[6] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proc. ACM MobiCom '10*, 2010, pp. 173–184.

[7] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: zero-effort crowdsourcing for indoor localization," in *Proc. Mobicom '12*, 2012, pp. 293–304.

[8] A. Jimenez Ruiz, F. Seco Granja, J. Prieto Honorato, and J. Guevara Rosas, "Accurate pedestrian indoor navigation by tightly coupling foot-mounted imu and rfid measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 1, pp. 178–189, jan. 2012.

[9] T. Wigren, "Adaptive enhanced cell-id fingerprinting localization by clustering of precise position measurements," *Transactions on Vehicular Technology*, vol. 56, no. 5, Sept. 2007.

[10] M. Azizyan, I. Constandache, and R. Roy Choudhury, "Surroundsense: mobile phone localization via ambience fingerprinting," in *Proc. ACM MobiCom '09*, 2009, pp. 261–272.

[11] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman, "Indoor location sensing using geo-magnetism," in *Proc. MobiSys '11*, 2011, pp. 141–154.

[12] H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef, and R. R. Choudhury, "No need to war-drive: unsupervised indoor localization," in *Proc. MobiSys '12*, 2012, pp. 197–210.

[13] N. Karlsson, E. Di Bernardo, J. Ostrowski, L. Goncalves, P. Pirjanian, and M. Munich, "The vslam algorithm for robust localization and mapping," in *Proc. ICRA 05*, 2005, pp. 24–29.

[14] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki, "Practical robust localization over large-scale 802.11 wireless networks," in *Proc. MobiCom '04*, 2004, pp. 70–84.

[15] J. Koo and H. Cha, "Autonomous construction of a wifi access point map using multidimensional scaling," in *Proc. Pervasive'11*, 2011, pp. 115–132.

[16] S. Yang, P. Dessai, M. Verma, and M. Gerla, "Freeloc: Calibration-free crowdsourced indoor localization," in *Proc. INFOCOM '13*, 2013, pp. 1–9.

[17] H. Lin, Y. Zhang, M. Griss, and I. Landa, "Wasp: an enhanced indoor locationing algorithm for a congested wi-fi environment," in *MELT'09*. Berlin, Heidelberg: Springer-Verlag, 2009, pp. 183–196.