WiNar: RTT-based Sub-meter Indoor Localization using Commercial Devices

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***Abstract*—WiFi time of flight (ToF) measurement has been supported recently by the wireless LAN protocols to improve WiFi localization. Specifically, the IEEE 802.11-2016 standard has a fine-time measurement (FTM) protocol that can be used to measure the WiFi signal round trip time (RTT). In this paper, we present the design and implementation of WiNar, a WiFi RTT-based indoor location determination system that combines the advantages of both fingerprint and ranging-based techniques to overcome the different challenges of indoor environments. Using commercial-off-the-shelf access points and mobile phones, WiNar leverages the propagation time of the wireless signal with a fingerprinting model to address the multipath, non-line-of-sight, signal attenuation, and interference challenges of the indoor environments. Moreover, when leveraging the round trip time measurements, WiNar does not require clock synchronization between the transmitter and the receiver. We discuss the different components of the system and its implementation on the Android operating system. Our results show that WiNar has a sub-meter localization accuracy with an average localization error of less than 0.86 meters for two different testbeds. This accuracy outperforms the performance of the traditional signal strength (RSS) fingerprinting technique by at least 38% and ranging-based multi-lateration technique by at least 148%. Finally, our system is also robust to heterogeneous devices.**

***Index Terms*—Indoor Localization, WiFi Localization, Time-based Localization, Time-based Fingerprinting, Fine Time Measurement.**

I. Introduction

The indoor localization problem has been an active research area over the years [1]–[9]. Unlike outdoor environments, where GPS can be used ubiquitously to determine an estimate for the user location within a few meters [10], indoor environments require more precise positioning to support various IoT-based and context aware applications [11]–[17]. Various solutions that involve multi-lateration, fingerprinting, angle of arrival, or time-based localization techniques, have been proposed to overcome the challenges related to indoor localization [18]–[23]. These solutions leverage different technologies such as WLAN, Bluetooth, UWB, visible light, ultrasound, and acoustic signals. The two most researched approaches have been those related to fingerprinting and time-based techniques.

Fingerprinting is an indoor localization technique that requires an environmental survey during an offline phase to obtain features of the physical signals where the localization system will be used [3], [24]–[26]. When the localization system is deployed, real-time, or online, sensory measurements are compared with offline measurements and a user location is estimated based on matching scores. Fingerprinting techniques are widely used with WLAN localization systems, where different signal properties like received signal strength (RSS) or channel state information (CSI) can be used as physical signal features [3], [24], [25]. The main challenge with these approaches, however, is that RSS values can easily be affected by signal attenuation from traveling through walls and other large obstacles. Another challenge is signal fluctuation due to multipath fading and indoor radio noise, as well as changes in the device hardware that lead to changes in the received RSS from APs due to different chips and antenna locations. Moreover, modern APs usually change their transmission power dynamically to accommodate different traffic and attenuation patterns. All of these issues have a negative impact on the accuracy of RSS fingerprinting-based techniques.

Time-based localization techniques, on the other hand, have been used for different indoor and sensor localization systems [27], [28]. They leverage the signal propagation time to estimate the distance between the transmitter and the receiver after multiplying it by the signal's velocity. Different approaches have been proposed to measure the signal propagation time as Time of Arrival (ToA) and Round Trip Time (RTT). Recently, the IEEE 802.11-2016 standard has introduced the Fine Time Measurement (FTM) protocol which supports the round trip time measurement and its Android API support has followed [29], [30]. With increasing support for this protocol in the commercial WiFi chipsets and mobile devices, it becomes a promising approach for providing high accuracy and easily deployable indoor localization systems.

Despite the promising improvement of time-based localization systems on the indoor localization accuracy, and its resilience to changes in transmission power and radio interference, they do not eliminate the significant localization errors in the indoor environments. This drawback is due to multipath propagation errors and non-line-of-sight transmissions when the direct path between the transmitter and receiver is not available. As a result, signals travel on longer indirect paths resulting in longer distance estimation [31]. These time-based ranging errors can be partially corrected through filtering and map matching techniques but they require obtaining a map for the area of interest in advance [32]. Also, multiple ranging measurements of the same location can be averaged to help

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filter out hardware and software noise, but cannot eliminate the multipath and non-line-of-sight effects which lead to distance overestimation [31].

In this paper, we present WiNar: a time-based fingerprinting indoor localization system that aims to combine the advantages of both fingerprinting and ranging-based techniques by using RTT as a physical signal feature. This approach enables WiNar to overcome the different indoor environment localization challenges and becomes more resilient to radio interference. Our system overcomes traditional time-based multi-lateration localization systems which suffer from the multipath propagation errors and non-line-of-sight transmissions resulting in distance overestimation. We also address the inaccuracies of these multi-lateration based localization systems which are affected by distance underestimations; these are situations where negative ranging distances can be returned by the ranging software under some conditions, especially when the mobile phone is close to the access point [31]. WiNar overcomes these challenges by leveraging the RTT values as a fingerprint profile and estimates the user location based on the similarity between the online and offline profiles.

WiNar works in two phases. The offline phase is when the RTT fingerprint map is collected at discrete locations in the building. The online phase is where a location is estimated based on a similarity between real-time sensed RTT measurements and the collected RTT Map data. WiNar uses different modules to handle the RF noise, provide similarity weights over the discrete grid locations, and localize the user in the continuous space.

We implement WiNar over different Android phones and evaluate its performance in two different testbeds: a 560m^2 college campus floor, and a 141m^2 work office floor. These testbeds represent a wide variety of environments that can make use of indoor positioning systems. We installed seven commercial Google WiFi access points (APs) in each testbed along with the presence of other traditional non RTT-enabled APs that can act as an added source of interference. Our results show that the WiNar system achieves a sub-meter localization accuracy for both testbeds with an average localization error of 0.86m and 0.84m for the two testbeds respectively. These results reveal an improvement over the traditional RSS fingerprinting accuracy by at least 38% and outperform the ranging based multi-lateration localization approach accuracy by at least 148%. This accuracy is maintained under heterogeneous devices which qualifies WiNar as a robust and accurate indoor localization technique.

The remainder of this paper is structured as follows. Section II provides a brief introduction on the IEEE802.11-2016 FTM protocol. In Section III, we provide a general overview of the WiNar system architecture and present its different components. Section IV evaluates the different parameters of the system and shows its overall performance compared to the other approaches. In Section V, we discuss related work. Finally, Section VI concludes the paper and discusses future work.

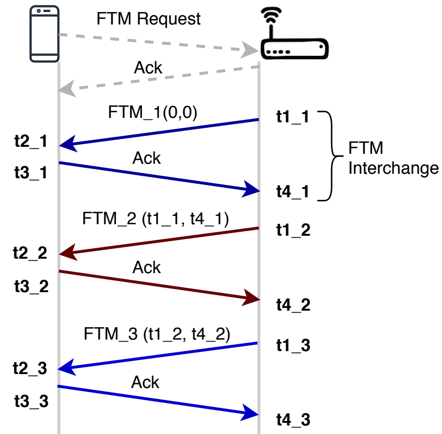


Fig. 1: FTM protocol overview.

II. FTM Protocol Background

IEEE 802.11-2016 has standardized the fine timing measurement (FTM) protocol that allows a station to accurately measure the round trip time (RTT) between it and another station. Fig. 1 shows a single burst of the FTM process with three FTM interchanges per burst. The protocol starts with an FTM Request packet sent from the initiating station (the mobile phone) to the responding station (the access point) to check the availability of the responding station to perform ranging and to negotiate the FTM process parameters. The responding station replies back with an ACK packet indicating its availability.

The protocol then follows by sending multiple FTM packets where the mobile device can obtain the RTT without knowing the clock offset by using the four send and receive timestamps of one FTM interchange as shown in Fig. 1. Specifically, the estimated round trip time between the source and the destination can be calculated as:

$$\mathrm{RTT} = (\mathrm{t4} - \mathrm{t1}) - (\mathrm{t3} - \mathrm{t2}) \tag{1}$$

The term $(t4 - t1)$ represents the estimated round trip time including the processing time at the mobile device while the term $(t3 - t2)$ represents the processing time at the mobile device. By subtracting the latter from the former, one can get the estimated round trip time between the source and the destination. Note that the transmit $(t1)$ and receive $(t4)$ timestamps at the access point side, of one FTM interchange, are transmitted to the mobile phone in the following FTM interchange. The last FTM interchange (FTM_3) is used only for timestamps transmissions and not for RTT estimations. Transmitting all timestamps to the mobile device allows the location estimation to be performed at the device side, preserving user privacy.

To provide a more accurate RTT estimation, the FTM interchanges can be repeated multiple times in the form of bursts. The FTM session parameters, like the number of bursts and the burst duration, are set in the negotiation phase of the

FTM protocol between the mobile phone and the access point [29]. The distance is obtained from the estimated RTT as:

$$\text{Distance} = \frac{\text{RTT} \times c}{2} \tag{2}$$

where c is the speed of light.

Note that the device performs RTT ranging to all RTT-capable APs in range. Traditionally, these have been used to multi-laterate the user location [31]–[33]. The WiNar system, on the other hand, leverages these RTT values, collected through the FTM protocol and available through the Android RTT API [30], as fingerprint features as we will show in the following section.

III. The WiNar Localization System

WiNar is a time-based indoor localization system that leverages the round trip time as a fingerprint feature to provide accurate location estimation. Our system overcomes the typical indoor environment localization challenges such as multipath interference and non-line-of-sight-related transmissions problems by leveraging the RTT values as a fingerprint profile and estimates the user location based on the similarity between the online and the offline profiles. WiNar utilizes the FTM protocol, introduced by the IEEE802.11-2016 standard and recently supported by commercial off-the-shelf access points and the Android mobile phones, as a protocol to measure the round trip time between the mobile phone and the access points. In the next subsections, we introduce the WiNar system architecture and then discuss WiNar components in detail.

A. System Overview

Fig. 2 shows the WiNar system architecture. The WiNar system works in two phases: The first phase is the **Offline Phase** where it divides the area of interest into discrete grid locations and builds the round trip time (RTT) fingerprint map. This fingerprint data collection phase needs to be done only once when the system is deployed for the first time. By using the round trip time from the different APs as an environment feature, the RTT fingerprint map becomes more resilient to the environment changes and radio interference which allows the fingerprint data to provide high accuracy localization over a long period of time (as we quantify in Section IV). This is compared to other fingerprint profiles, e.g. using the RSS, which can be easily affected by the existence and removal of other radio noise sources and access points as well as changes in the APs transmit powers.

The second phase of WiNar is the **Online Phase**, where it estimates the user location based on the measured round trip time values to the different access points and the generated RTT fingerprint map.

The WiNar system consists of multiple key modules that belong to the offline and online phases as shown in Fig. 2. The **RTT Collector** module is used to scan for the APs and collect the associated RTT values at the different locations in the area of interest during both the offline and online phases. The **Pre-processing** module arranges the collected RTT values to construct the RTT feature vectors. The **RTT Map Builder** module constructs the RTT fingerprint from the estimated RTT to the different APs in the area of interest. The **Single Sample Estimator** module works during the online phase to calculate the similarity weight of each fingerprint location given the currently estimated RTT vector from different access points at the unknown user location. The **Multiple Samples Estimator** module combines the number of estimates output by the *Single Sample Estimator* to get a more accurate location estimation in the continuous space.

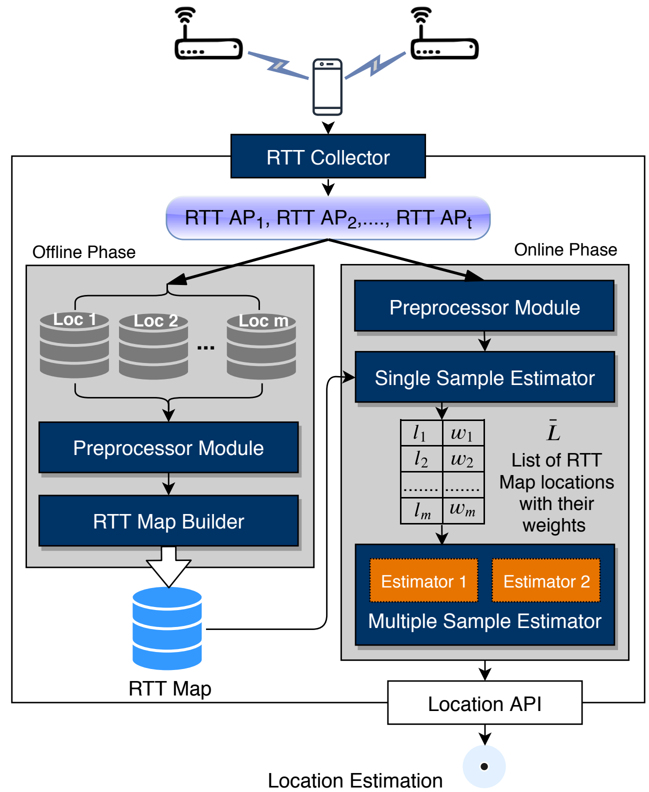


Fig. 2: The WiNar system architecture.

We will now discuss the functionality of these modules in more detail.

B. System Details

We start by introducing the mathematical model of the WiNar system. Without loss of generality let $\mathbb{X}$ be a two-dimensional physical space. At each location $x_i \in \mathbb{X}$ we can get the round trip times RTT from t access points in the area of interest. We denote the t-dimensional round trip time space as $\mathbb{R}$. The RTT fingerprint map $\mathbb{M}$ contains m entries, where the i^{th} entry contains the coordinates of a discrete location $l_i \in \mathbb{X}$ and a fingerprint profile $p_i \in \mathbb{R}$. Let $r \in \mathbb{R}$ be an RTT ranging sample vector that contains the round trip time to the t access points during the online phase.

1) Pre-processing Module: The pre-processing module is used to convert the input RTT vector to a **fixed length** feature vector by mapping each collected RTT value to its entry in this vector. Since not all of the t access points installed in the area of interest can be heard in every scan at the different locations, this module assigns the RTT value of 2×10^{-4} milliseconds (which corresponds to 60 meters in the distance domain) to the APs that are not heard in a specific scan. This value is selected to be larger than any of the collected RTT values. The intuition is that a not heard AP is supposed to be far away from the current location. Therefore, it should be assigned a high RTT value.

We also observed that under some conditions, mainly when the mobile phone is too close to the access point that is performing the ranging to, the Android API can return negative estimated ranging distances. These negative distance values are due to the internal calibration of the WiFi cards or the multipath compensation algorithms that process the measurements in firmware before they are delivered to the driver. These negative ranging values usually cause a problem for traditional multi-lateration algorithms [31]. However, since WiNar is a fingerprint-based technique, these negative values are implicitly handled as being part of the fingerprint of a particular location and hence do not affect the system accuracy.

2) The RTT Map Builder Module: The RTT Map Builder module constructs the WiNar fingerprint. Specifically, for each fingerprint location l, it stores the coordinates of the location as well as the average of all the RTT measurements performed at this location for each AP. In particular, at each fingerprint location l, a vector $p = \langle \text{Avg}\,\text{RTT}_1, \text{Avg}\,\text{RTT}_2, ..., \text{Avg}\,\text{RTT}_t \rangle$ is stored to reflect the RTT fingerprint.

3) Single Sample Estimator Module: During the online phase, the goal of this module is to use the received RTT ranging vector at an unknown location to estimate the user location.

Specifically, given an RTT ranging sample vector $r \in \mathbb{R}$, the Single Sample Estimator module returns a score for each fingerprint location representing the likelihood of the user being at that location.

More formally, the module returns a list of the grid locations and their weights $(\bar{L}(l_i, w_i))$, where $1 \leq i \leq m$, in the RTT fingerprint map ordered by their score of similarity (weight) in descending order, where the weight of the location l_i is given by:

$$\text{Weight}(l_i) = \frac{1}{\text{Euclidean Distance}(p_i, r)^d} \tag{3}$$

where d is a parameter to the system.

This ordered list of weights reflects the similarity between the current single ranging sample r and the RTT profile vectors p over the discrete locations of the RTT fingerprint map $\mathbb{M}$.

4) The Multiple Samples Estimator Module: To give a more accurate user location estimation in the continuous space, the *Multiple Samples Estimator Module* processes s RTT ranging sample vectors $r \in \mathbb{R}$ together, where s is a parameter to the system. Specifically, given the ordered list of grid locations and their similarity weights $\bar{L}_j$ obtained from the *Single Sample Estimator* module for each ranging sample vector j, where $1 \leq j \leq s$, this module fuses these discrete locations to output a more accurate user location estimation in the continuous space. We present two different fusion techniques:

a) Technique 1: For each ranging sample $r_j \in \mathbb{R}$, $1 \leq j \leq s$, an initial location estimate x_j in the continuous space is first calculated by taking the weighted average of the K most probable fingerprint locations. More formally:

$$x_j = \frac{\sum_{n=1}^{K} [\bar{L}_j(w_n) \times \bar{L}_j(l_n)]}{\sum_{n=1}^{K} \bar{L}_j(w_n)} \tag{4}$$

Given these initial location estimates x_j, $1 \leq j \leq s$, the final fused location estimate is calculated as the weighted average of these initial locations, taking the highest of the weights of each estimate as its weight. More formally, the final location estimate x is calculated as:

$$x = \frac{\sum_{j=1}^{s} \text{weight}(x_j) * x_j}{\sum_{j=1}^{s} \text{weight}(x_j)} \tag{5}$$

where the weight of x_j is the weight of the first location in the ordered list $(\bar{L}_j)$

$$\text{weight}(x_j) = \bar{L}_j(w_1) \tag{6}$$

b) Technique 2: Unlike the previous fusing technique that leverages each ranging sample vector individually to get an initial location estimation, this technique calculates a total weight vector by summing the weights of each ranging sample vector r over the s ranging samples as:

$$\text{Total weight}(l_i) = \sum_{j=1}^{s} \bar{L}_j(\text{w}_i) \tag{7}$$

The final location estimation x is calculated as the weighted average of the fingerprint locations l_i, $1 \leq i \leq m$ using these $total\,weight$ values as:

$$x = \frac{\sum_{i=1}^{m} \text{Total weight}(l_i) * l_i}{\sum_{i=1}^{m} \text{Total weight}(l_i)} \tag{8}$$

By leveraging multiple ranging samples and a weighted average approach to calculate the location estimation, this enables WiNar to be resilient to the environment dynamics by dominating the noisy weights, resulting from noisy ranging samples due to the environment dynamics or other hardware and software noises, by the weights that are calculated from the other accurate majority of the collected ranging samples. This weighted average approach enables WiNar to estimate a robust and accurate location estimation in the continuous space.

IV. System Evaluation

In this section, we evaluate the performance of WiNar in two typical indoor environments: a college campus building floor and a work office floor. We start by describing the testbeds and the data collection procedure. Next, we analyze the effect of different parameters on the WiNar performance. Finally, we present the overall system performance and compare it with the traditional RSS fingerprinting and time-based multi-lateration approaches.

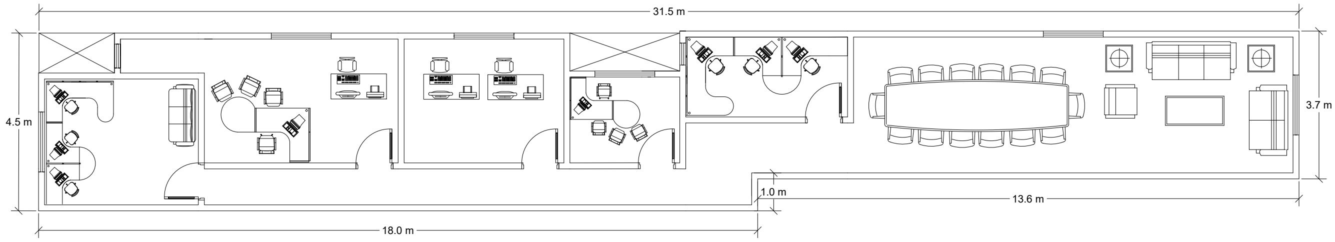


Fig. 3: Testbed 2 floor plan (work office).

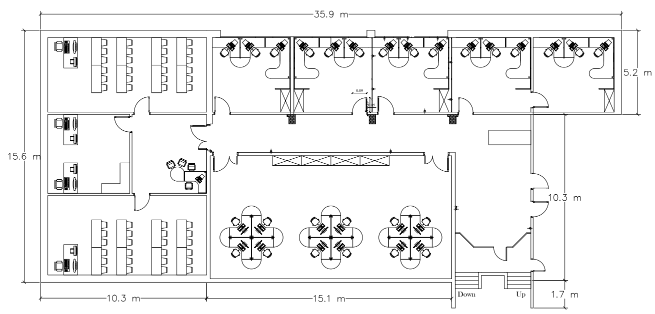


Fig. 4: Testbed 1 floor plan (college campus).

TABLE I: Testbeds Summary

Testbeds Parameters	Testbed 1	Testbed 2
Area	$15.6m \times 35.9m$	$4.5m \times 31.5m$
Number of RTT APs	7	7
Average heard APs by Pixel XL	2.86	3.07
Average heard APs by Pixel 2XL	4.47	4.71
Training Points	143	76
Testing Points	30	17

A. Experimental Setup and Data Collection

The performance of the WiNar system is analyzed in two testbeds. Table I summarizes the testbeds. The **first testbed** (Fig. 4) is a floor at our college campus that contains nine rooms/labs connected with a large corridor and covers an area of 560m^2. The **second testbed** (Fig. 3) is an office building that consists of five rooms and a large meeting room, all connected with a long corridor and covers an area of 141m^2.

For both environments, we use a wireless network consisting of seven Google WiFi APs uniformly distributed over the experiment floor area and two mobile phones: a Google Pixel XL and a Pixel 2XL running Android API level 28 as receivers. Other APs that do not support RTT are also installed in both testbeds.

The fingerprint grid locations are taken to be one meter apart from each other in the building areas we have access to (we evaluate the effect of changing the fingerprint density later in this section). The first testbed has 143 fingerprint locations while the second has 76 locations. 100 ranging samples are performed at each fingerprint location. ***Independent test sets collected at different days, locations, and by different persons are used for testing.*** Each location has a minimum coverage of one Google WiFi AP.

TABLE II: System and Evaluation Parameters

Parameter	Possible Values	Testbed 1 default val.	Testbed 2 default val.
Ranging Samples	[5:100]	100	100
Weight Func. Pow. (d)	[1:5]	3.5	3.5
Estimator Approach	Estimator 1, 2	1	1
Num. Neighbours K	[1:10]	1	1
Access P. Density	[1:7]	7	7
Fingerprint Gap	1, 2, 3 m	1 m	1 m

B. Effect of Changing WiNar Parameters

In this section, we show the effect of changing different parameters of the WiNar system on the localization accuracy. Table II summarizes the parameters and their default values. We use Testbed 1 as the main testbed for reporting the results and provide the overall accuracy of Testbed 2 in the overall system comparison in Section IV-D. Note that exactly the same set of default parameter values are used for the two testbeds, highlighting WiNar robustness to different environments.

1) Impact of Number of Ranging Samples: Fig. 5 shows the performance of the WiNar system while varying the number of the ranging samples for the first testbed. The results show that as the number of the ranging samples increases, the WiNar system accuracy improves as the noise in the RTT ranges are averaged out. WiNar can achieve a sub-meter localization accuracy of 0.86 meters with an average delay time of less than 2.7 milliseconds per location estimate. Note that the average time per location estimate increases linearly with the number of ranging samples used.

Depending on the application where the WiNar system will be used and the accuracy level required, a lower number of ranging samples can be used to reduce the latency. The localization latency can also be reduced by leveraging the initial ranging samples to output an initial rough location estimation that can be improved by accumulating the remaining ranging samples over time.

2) Impact of Weighting Function Power: Fig. 6 shows the effect of increasing the euclidean distance power of the weighting function (parameter d in equation 3) on the average localization error and average time per location estimate. The results show that increasing the weighting function power leads to increasing accuracy until we reach about 3.5 then the accuracy decreases while the average time per location estimate remains constant. We set the default power to 3.5.

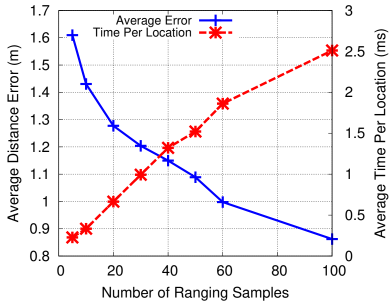


Fig. 5: Effect of changing number of the ranging samples on the average localization error and time per location estimate.

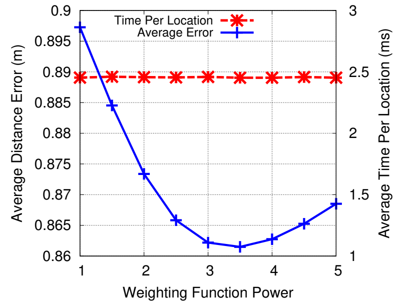


Fig. 6: Effect of changing the euclidean distance power (d) of the weighting function on the average localization error and time per location estimate.

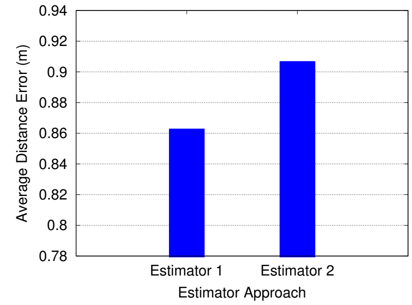


Fig. 7: The average localization error for the two different multi-samples fusion techniques.

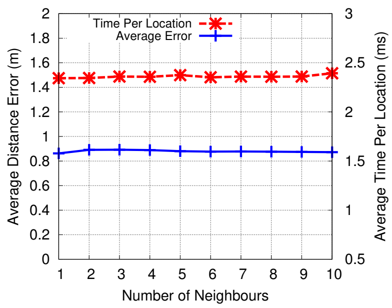


Fig. 8: Effect of changing the number of neighbours k for estimator 1 on the average localization error and time per location estimate.

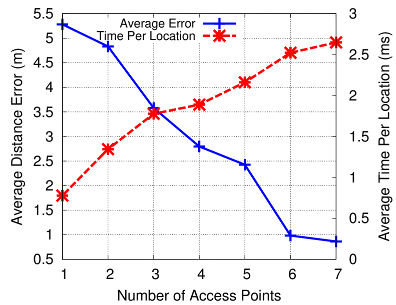


Fig. 9: Effect of changing the density of the access points on the average localization error and time per location estimate.

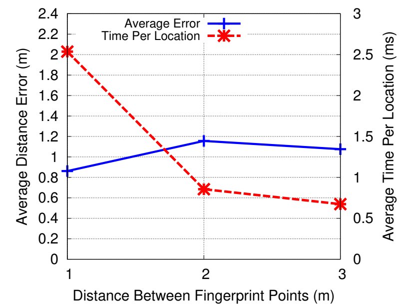


Fig. 10: Effect of changing the fingerprint locations density on the average localization error and time per location estimate.

3) Impact of the Multi-samples Fusion Technique: Fig. 7 shows the effect of the the different multiple samples estimators discussed in Section III. The figure shows that the performance of the first and second estimators is comparable with a slight advantage to Estimator 1.

4) Impact of the Number of Nearest Neighbours: Fig. 8 shows the impact of increasing the number of nearest neighbors, k, on the average localization error and time per location estimate. The figure shows that the performance is not sensitive to the number of used neighbors. Therefore, we choose to use $k = 1$ to reduce computation cost.

C. Robustness Experiments

In this section, we evaluate WiNar performance robustness using two experiments: reducing the density of the access points and reducing the number of the fingerprint points.

1) Impact of Access Points Density: Fig. 9 shows the effect of increasing the access points density on the average localization error and average time per location estimate. The density is reduced by manually removing APs while maintaining their uniform distribution over the testbed area. The results show that increasing the APs density leads to increasing accuracy. This can be explained by noting that the number of APs heard per scan increases with the increase of the number of APs installed in the area of interest. The time per location estimate increases linearly with the number of APs installed with worst case of less than 2.7 milliseconds per location estimate.

2) Impact of Fingerprint Points Density: Fig. 10 shows the effect of increasing the distance between the fingerprint grid locations on system performance.

The results show that decreasing the fingerprint density, i.e. increasing the distance between fingerprinting points, has a sub-linear effect on accuracy. Specifically, even when the fingerprint points are spaced every three meters, WiNar average accuracy is about 1m. This highlights the advantage of WiNar in requiring lower overhead compared to traditional RSS fingerprinting techniques that usually require higher fingerprinting densities.

D. Overall System Performance and Comparative Evaluation

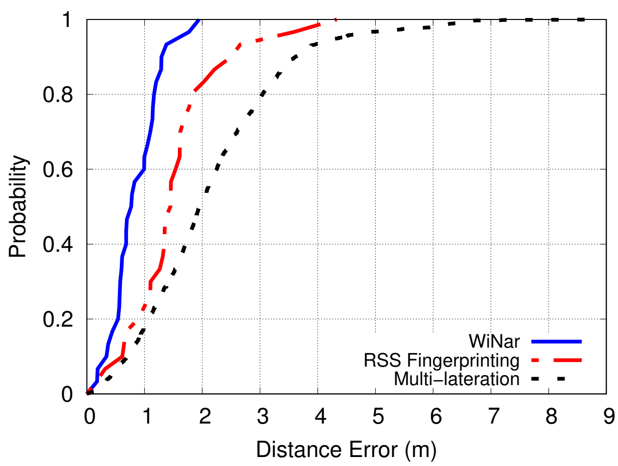
In this section, we show the performance of the whole WiNar system compared to two related approaches: RSS fingerprinting and RTT multi-lateration. The RSS fingerprinting technique uses the same modules as WiNar but with RSS instead of RTT.

We use the default values of the system parameters indicated in Table II.

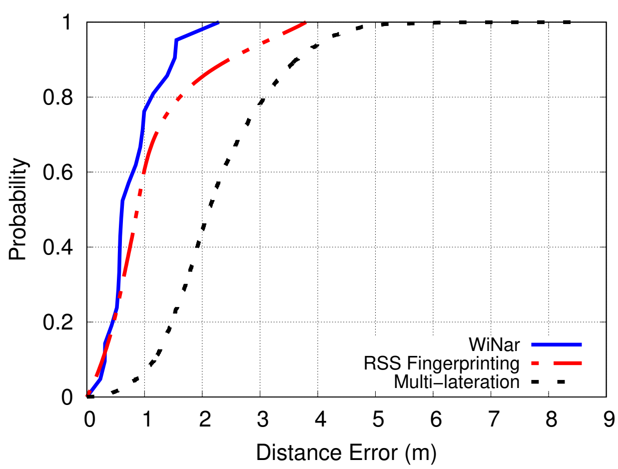
Fig. 11 shows the performance comparison for the two testbeds respectively while Table III summarize the results.

TABLE III: Average accuracy and percentiles comparison between different approaches as WiNar, RSS fingerprint and multi-lateration in the two testbeds (errors in meters).

	Testbed 1 (college campus floor)					Testbed 2 (work office floor)				
	Average	Std Dev	50^{th} Percentile	90^{th} Percentile	100^{th} Percentile	Average	Std Dev	50^{th} Percentile	90^{th} Percentile	100^{th} Percentile
WiNar	**0.86m**	**0.43m**	**0.77m**	**1.37m**	**1.95m**	**0.84m**	**0.51m**	**0.62m**	**1.55m**	**2.29m**
RSS Fingerprint	1.55m (-80.23%)	0.87m (-102.33%)	1.45m (-88.31%)	2.64m (-92.7%)	4.33m (-122.05%)	1.16m (-38.09%)	0.94m (-84.31%)	0.91m (-46.77%)	2.37m (-98.06%)	3.80m (-65.93%)
Multi-lateration	2.14m (-148.84%)	1.26m (-193.02%)	1.95m (-153.25%)	3.61m (-163.5%)	8.86m (-354.36%)	2.28m (-171.42%)	0.98m (-92.15%)	2.12m (-241.94%)	3.63m (-134.2%)	8.62m (-276.4%)



(a) Testbed 1.



(b) Testbed 2.

Fig. 11: Comparison between the error CDF for WiNar, RSS fingerprinting and Multi-lateration for the two testbeds.

The WiNar system can achieve a sub-meter localization accuracy with an average localization error of 0.86 meters for the first testbed and 0.84 meters for the second testbed. This is better than RSS fingerprinting by more than 80% for the first testbed and more than 38% for the second testbed. This comes also with a decrease in the worst-case error by more than 122% for the first testbed and more than 65% for the second testbed.

Comparing the WiNar system performance to the time-based ranging multi-lateration localization techniques shows that WiNar can achieve a better localization accuracy by more than 148% for the first testbed and more than 171% for the second testbed. The worst-case error is decreased by 354% and 276% for the first and second testbeds respectively in this case.

Fig. 12 also shows the effect of the heterogeneity of the devices on the performance of WiNar and RSS fingerprinting approach. The figure shows that WiNar is more robust to device heterogeneity compared to RSS-based techniques. This can be explained by noting that changes in the device hardware lead to changes in the received RSS from the APs (due to different chips, form factors, antenna locations, etc). This has a lower effect on the calculated RTT values.

The difference in the performance of WiNar for the two phones is related to two factors. First, the number of ranging samples the mobile device can perform successfully out of the one hundred ranging samples. Second, the number of access points that the mobile device can successfully hear and perform ranging to in each ranging sample individually. Fig. 13 shows the probability distribution of the number of successful ranging samples the two mobile devices are able to perform. From this figure, we can see that the mobile device Pixel 2XL is able to perform more successful ranging samples compared to the other device Pixel XL. Also from Fig. 14, which shows the quartiles (0^{th}, 25^{th}, 50^{th}, 75^{th}, 100^{th} percentiles) box plot for the number of successfully heard access points in each ranging sample for both the mobile devices, we can see that the Pixel 2XL is able to hear and perform ranging with more access points in each ranging sample and hence achieving better localization accuracy.

These results confirm the advantages of using RTT fingerprinting compared to RSS fingerprinting or multi-lateration. This is due to the ability of RTT fingerprinting to tolerate the multi-path effects, non-line-of-sight transmission, radio interference, changes in the APs transmit power, and device heterogeneity.

V. Related Work

Many systems have been developed over the years to tackle the problem of indoor localization. Ultrasound based localization systems leverage the time of flight of the ultrasound signals and the sound velocity to estimate the distance between the transmitter and the receiver [34], [35]. These systems usually require special infrastructure to operate, which increases their cost. Visible light based localization systems

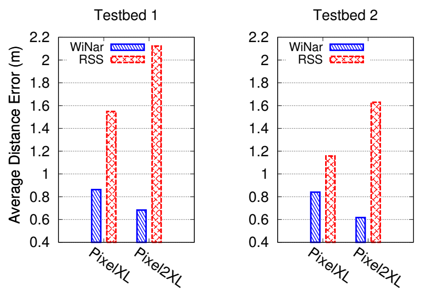


Fig. 12: Effect of changing the device on WiNar and RSS fingerprinting localization accuracy on the two testbeds.

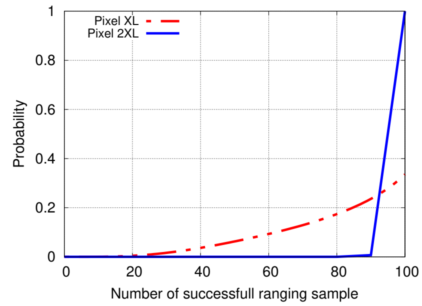


Fig. 13: probability distribution of the number of successful ranging samples the mobile devices are able to perform out of the one hundred ranging sample in testbed 1

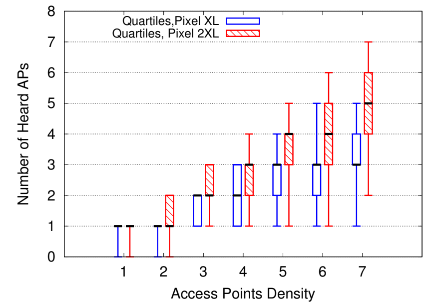


Fig. 14: The quartiles box plot of the number of access points heard in each ranging sample for the different access point densities for testbed 1.

use light sensors to measure the angle of arrival (AOA) of the light signals transmitted by LED emitters [36], [37]. The main drawback of these systems is that they can only operate under the availability of the direct line of sight between the transmitter and the receiver.

Recently, WiFi-based localization systems have gained momentum due to the ubiquity of WiFi devices and APs [38]–[42]. This reduces the cost of these systems and makes them easy to deploy without the need for additional infrastructure. In the rest of this section, we discuss signal the strength- and time-based WiFi localization systems.

A. Signal Strength-based Systems

Received Signal Strength (RSS) localization approaches use the signal attenuation of transmitted signals to estimate the distance between the transmitter and the receiver [43]–[45]. RSS model-based techniques suffer from poor localization accuracy, especially in non-line-of-sight conditions, due to the signal attenuation resulting from transmission through walls and other obstacles as well as RSS fluctuation due to multipath fading and indoor noise.

To overcome these challenges, RSS fingerprinting approaches work in two phases: the offline and online phase [3], [24]. The offline phase is used to collect a fingerprint of the APs in the area of interest at different discrete locations. During the online phase, the systems match the current heard RSS values to those stored in the fingerprint. Different systems use different features for their fingerprint. Similarly, the channel state information (CSI) provides more fine-grained and detailed information about the received signal of the channel in different frequencies and between separate transmitter-receiver antenna pairs [46], [47]. Therefore, they are able to provide more accurate estimates compared to RSS-based systems. Nonetheless, they require special hardware to capture the state information. Moreover, both RSS and CSI values are easily affected by the dynamic changes of the APs transmit power, which is a common feature of modern APs [48]. In addition, they are sensitive to the device used to construct the fingerprint.

B. Time-based Systems

Time-based localization systems, on the other hand, leverage the wireless signal propagation time to estimate the distance between the sender and the receiver given the signal velocity [49]. Time of Arrival (ToA) is a one-way measurement where the receiver leverages the transmit timestamp (usually included in the transmitted packet) and the receive timestamps to measure the signal propagation time. ToA technique requires strict clock synchronization between the transmitter and the receiver to estimate the propagation time accurately [50].

Time Difference of Arrival (TDoA) techniques leverage the difference between the signals propagation times that are transmitted from three or more transmitters to estimate the user location. Unlike the ToA technique, the TDoA requires strict clock synchronization between the transmitters only [51], [52].

Round trip time (RTT) is a two-way measurement technique where one station responds back to the other with a packet containing the receive and transmit timestamps. The other station leverages this information to calculate the round trip time [33], [53], [54]. Unlike ToA, the RTT technique does not require strict clock synchronization. Traditional multi-lateration systems that leverage the RTT measurements to obtain the location estimate suffer from relatively poor localization accuracy due to processing offsets, multipath effects and non-line-of-sight transmissions that lead to overestimated range values [31]. As we quantified in the evaluation section, WiNar inherently captures these effects in its fingerprint and hence leads to better accuracy.

VI. Conclusion

We presented WiNar, an indoor location determination system that combines both the advantages of the fingerprinting and the time-based ranging localization techniques. We showed how the different modules of WiNar overcome the indoor environment challenges such as non-line-of-sight, multipath and signal interference.

We evaluated the WiNar system in two different testbeds. We showed that WiNar system can achieve a consistent sub-meter localization accuracy of 0.86 meters and 0.84 meters for the first and second testbeds respectively. We also compared the WiNar system performance to the RSS fingerprinting and time-based multi-lateration localization techniques. Our results show that the WiNar system can achieve a better localization accuracy compared to the RSS fingerprinting by more than 38% for the two testbeds. This increases to more than 148% as compared to the RTT multi-lateration based technique.

As part of our ongoing research work, we aim to reduce the overhead of collecting the RTT fingerprint data as well as combine RTT and RSS fingerprinting for better accuracy.

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