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Applicability and challenges of indoor localization using one-sided round trip time measurements

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Applicability and Challenges of Indoor Localization Using One-Sided Round Trip Time Measurements

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ABSTRACT

Radio Frequency fingerprinting, based on WiFi or cellular signals, has been a popular approach for localization. However, adoptions in real-world applications have confronted with challenges due to low accuracy, especially in crowded environments. The received signal strength (RSS) could be easily interfered by a large number of other devices or strictly depends on physical surrounding environments, which may cause localization errors of a few meters. On the other hand, the fine time measurement (FTM) round-trip time (RTT) has shown compelling improvement in indoor localization with ~1-2 meter accuracy in both 2D and 3D environments [13]. This method relies on the WiFi standard 802.11mc implemented in APs (two-sided RTT). However, one obstacle is that the number of APs satisfying this 802.11mc requirement is limited because the frequency of an AP upgrade to a newer version is not as frequent as other electrical equipment. The publication of Google's Android 12, supporting one-sided RTT, enables the RTT applicability in almost all AP models. This article synthesizes multiple experiments to evaluate the feasibility of one-sided RTT in indoor localization and describes in detail the effects of various factors such as different AP models, phone models, and burst sizes on the performance of localization accuracy. Despite existing challenges of applying one-sided RTT, this approach is lightweight, scalable, and could easily be utilized by wearable devices to provide reasonably accurate indoor localization.

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CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile devices*;

KEYWORDS

Indoor localization, One-sided RTT

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1 INTRODUCTION

These days, people mostly use GPS to locate their current positions when traveling by car, bike, or foot. However, using GPS for indoor localization is troublesome as the navigation does not work well inside buildings [15]. Accurately determining indoor positioning, especially in environments where GPS signals are unreliable, has various potential applications and has garnered considerable interest over time. Recent advancement in this domain involves fine time measurement (FTM) of round trip time (RTT), proposed in the 2016 revision of the IEEE 802.11 Wi-Fi standard (known as IEEE 802.11mc) [6]. One notable limitation of the FTM RTT approach is the restricted adoption of the IEEE 802.11mc protocol among access points (APs). To address this constraint, an alternative approach utilizes a simpler protocol, called one-sided RTT, which solely measures the time difference between message transmissions and acknowledgment receipts [4]. Nevertheless, the omission of the turnaround time introduces an unknown factor - the AP's processing time - referred to as $proc_{time}$, significantly affecting reported measured distances. In this paper, we initially provide a brief overview of indoor localization methodologies. Subsequently, we describe the operational mechanics of FTM RTT and one-sided RTT. Finally, the paper presents the empirical findings derived from our experiments employing one-sided RTT with the aim of feasibility assessment of this approach for indoor localization. Overall, our paper contributes the following:

- A four-day data collection was performed at our school from multiple locations with various environments. This resulted in 334 separate measurements, each lasting a minute. A minute of data collection gives approximately 155 different data points, which gathers a total of 51770 different data points.
- An evaluation based on multiple factors regarding the applicability of one-sided RTT for indoor localization was executed. These factors stem from different AP models, smartphone models, the utilization of Dynamic Frequency Selection (DFS) or Non-DFS, various burst sizes, as well as the range of distances where one-sided RTT can still be applied. During the feasibility assessment of applying one-sided Round-Trip Time (RTT) for indoor localization, the effectiveness of localization can be relaxed by evaluating the efficacy of ranging reports on the distance between the Access Point (AP) and the smart device.

2 RELATED WORK

2.1 Traditional indoor localization methods

Approaches could be categorized as using or not using additional sensors, apart from a mobile device which is carried by most people. These sensors could either be external (e.g., BLE [1] or RFID [14] tags) or internal (e.g., gyroscope or accelerometer [2, 8, 9]). The primary limitation of such approaches is that they require customized hardware or software installation, which limits their scalability and wide distribution. Besides using IMU-based motion data, other works also exploit RSSI for localization [7, 12]. However, most such work assumes that the RSSI and the distance to the AP are inversely proportional [10]. Other approaches use fingerprinting [11], where collected RSSI data is stored in a database during the offline phase, then infer location in the online phase. One major drawback of this approach is the alteration of physical areas such as the removal of APs, addition of new APs, emergence of new objects, etc., all these factors cause the fingerprint database collected in the past to become outdated and significantly reduce the accuracy. In addition, constructing the fingerprint database requires engaged user participation with an extremely heavy workload and computation.

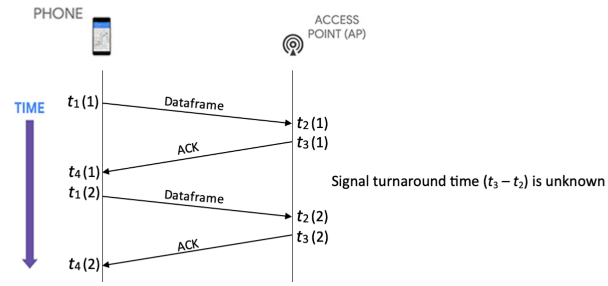

Figure 1: One-sided RTT operations.

2.2 Fine time measurement RTT

FTM RTT provides a mechanism for a smart device to estimate its distance to a Wi-Fi AP [4]. It reports half of the round-trip time of an RF signal, minus the turn-around time, then multiplied by the speed of light. The internal clocks are usually asynchronous between devices and APs since the timestamp difference is reversed when the signal travels in the opposite way.

The localization accuracy of RTT is more stable than the RSSI fingerprint as it is computed right away at the time of measurement. Whereas, the fingerprint approach must be handled with an outdated database when the surrounding environment is changed. RTT works pretty well under line-of-sight (LOS) conditions and with no obstacles between the device and the AP. The reason is that RF signal speed is decreased when they pass through objects. As a result, the RTT measurement normally could not be directly employed as distance measurement, but go through some observation or filter models to resolve the target position. In addition, two-sided RTT requires the cooperation of the APs. It has a scaling issue when APs may become overloaded if many smartphones simultaneously try to determine their positions.

2.3 One-sided RTT

Since the number of APs that implement 802.11mc is still limited and two-sided RTT requires APs' cooperation, a simpler mechanism by solely using one-sided RTT to calculate the difference between the time of sending and receiving the Ack of the message could be utilized [4] as illustrated in figure 1. This approach is applicable for most of the current APs, and due to the one-sided feature, it also reduces the APs' load and is still able to operate when many localization queries are requested at the same time. One drawback compared with two-sided RTT is that the processing time $proc_{time}$has to be subtracted from the reported measurements. These $proc_{time}$values are usually large, depending on various factors, and may translate to thousands of meters offset(e.g., 2400m and 3000m for Google pixel 5 and Google Pixel 7 phones, respectively) because the "turn-around time" is roughly eliminated. From the initial testing data that we collected, these $proc_{time}$values are changing gradually which may be affected by the dynamic surrounding environment. One advantage is that the changing degree is not drastic, so this offset is stable for some short duration and could be sufficient for inferring the device locations.

3 RESEARCH METHOD AND DATA COLLECTION

To evaluate and respond to the most important question, "Can one-sided RTT be applied for indoor localization?", we conducted two main experiments to answer: (1) "Is there processing time, $proc_{time}$? stable for some short duration?" This is a crucial factor in determining the feasibility of executing the approach. Since the distance will be estimated by the product of travel time and speed of light, if $proc_{time}$is unstable, it will lead to significant inaccuracies in ranging measurement. On the other hand, if this value is somehow static over a short duration (~30 seconds), we can consider the error as a constant offset that could be eliminated to infer the correct distance between APs and smart devices; (2), "Is it possible to discern varying distances from the access point?" By conducting experiments with ground truth distances incrementally increasing in 3-meter intervals, we can evaluate whether one-sided RTT is susceptible to changes in ranging.

To answer these two key questions, we set up a standard environment for this experiment using a Google Pixel 5, with the burst size selected at the default value of 8, and testing with the WifiRttScan Android application [3]. In addition, for each set of experiments, after assessing the feasibility of the one-sided RTT solution, additional experiment sets will evaluate the localization performance using different parameters. Testing these parameters includes experiments on different generations of APs, different phone models (Pixel 5 and Pixel 7), different apps (WifiRttScan [3] and WifiRttScanX [5]), different burst sizes (2, 4, 8, 16, 32), and whether Dynamic Frequency Selection (DFS) is used or not. Details of conducting this experiment will be presented in section 4.

The locations of the experiments are categorized into four groups, namely “Room”, “Architecture Unique”, “High Traffic” and “Normal”. The “Room” contains seminars and classrooms around the campus. These rooms commonly have up to two APs installed, providing good AP coverage. “Architecturally Unique” locations seek to identify locations where ranging may not be as straightforward, such as floors with double-height ceilings and open-air locations. “High Traffic” locations refer to areas with high footfall on campus. It is important to clarify whether AP can still maintain a stable $proc_{time}$under "High Traffic" locations or not. Lastly, the "Normal" represents rooms or pathways with average density.

Additionally, we manipulated the ground truth data derived from APs and endeavored to ascertain the capability of one-sided RTT in measuring various distances from the APs. The assessment employed a laser rangefinder positioned on the floor to determine the distance to the point directly beneath the AP. Similarly, data was collected by a mobile device placed on the floor at the location indicated by the laser rangefinder. Measurements were conducted at 3-meter intervals, ranging from 0 meters to 21 meters.

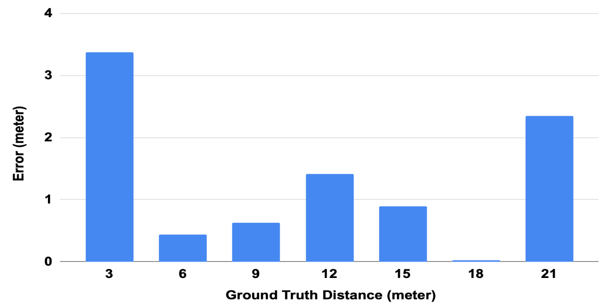

Figure 2: Ranging errors with various ground truth distances to AP.

4 EXPERIMENT RESULTS

4.1 Can one-sided RTT be applied for indoor localization?

Figure 2 represents the distance errors resulting from various ground truth distances to access points. Considering the reported measurement at 0 meters as the baseline, subsequent reported measurements at 3-meter intervals are subtracted from this baseline value to determine the distance errors. Apart from the ground truth distances of 3 meters and 21 meters, which exhibit errors of 3.2 meters and 2.3 meters, respectively, all other errors remain well below 1.5 meters. The error for the ground truth distance of 3 meters may be attributed to the selection of 0 meters as the baseline offset, while the error of 2.3 meters for the 21-meter ground truth distance is notably favorable. These findings indicate that one-sided RTT possesses the capability for ranging, which is a prerequisite for indoor localization.

To further comprehend the capabilities of one-sided RTT, its performance is compared against RSSI. The experiment was conducted to simultaneously measure the average RSSI and distance measurements from one-sided RTT over 30 seconds. The distance to the Aruba AP-535 access point increased gradually from 3 to 21 meters, with 3-meter intervals. Figure 3 illustrates that RSSI rapidly declines to -80 dBm. This signal level is generally deemed unsuitable for indoor localization when the distance is greater than 12 meters. On the other hand, one-sided RTT yields an encouraging result of 1.3 meters as the average measurement error across all measurements.

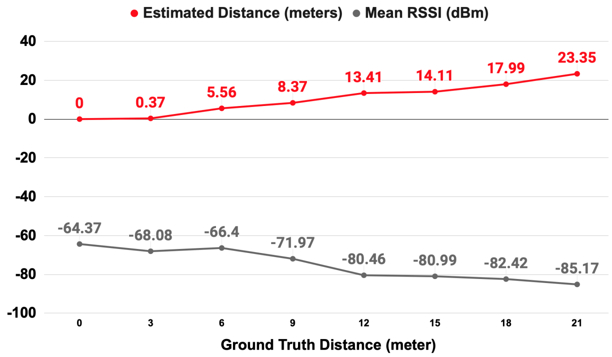

Figure 3: One-sided RTT vs. RSSI capability in measuring long distances.

Day	Mean Estimated Range (meters)	Mean S.D. (meters)
1	2457.66	2.23
2	2457.72	2.62
3	2458.71	1.93
4	2455.24	1.97

Table 1: Ranging measurements on various days.

4.2 Is the processing time $proc_{time}$ stable?

4.2.1 Stable $proc_{time}$. Based on the data collected across multiple days, it can be inferred that the processing time $proc_{time}$ remains stable. This results in consistently large offsets presented in the one-sided RTT measurements. Table 1 presents the ranging measurement of a stationary device to the access point. The experiment was conducted over four days to assess the stability of $proc_{time}$ across various time points. For data cleaning, mean ranging measurements were calculated after removing outliers and data points with a standard deviation higher than 4 meters.

Based on the above results, measurements ranged between 2455.24 meters and 2458.71 meters aligning with the known 3-4 meter accuracy of one-sided RTT. This finding suggests that these measurements could serve as a constant offset on the mobile device to rectify the reported large measurements stemming from the AP's processing time during one-sided RTT operations.

4.2.2 Effects of different apps, phone models, and burst sizes on $proc_{time}$. Numerous factors could influence the processing time $proc_{time}$, resulting in considerable discrepancies in reported distance measurements. Failure of rigorous consideration of these factors could lead to variances of up to hundreds of meters since the distance is measured by the ($proc_{time}$* speed of light). Factors contributing to this variance include phone models, burst sizes, and the applications to implement distance calculation ([3] and [5]).

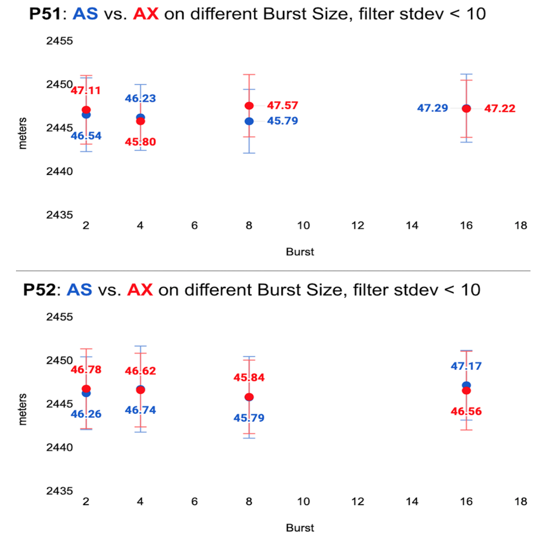

Figure 4: Mean and standard deviation of ranging measurements on various factors of Pixel 5 phone.

In this experiment, a mobile device was positioned directly beneath a 2-meter high access point to acquire reported ranging measurements. Figures 4 and 5 illustrate the average ranging which was coupled with the standard deviation as reported by [3] (denoted by AS in blue color) and [5] (denoted by AX in red color) on Pixel 5 and Pixel 7 respectively. The x-axis denotes various burst sizes, while the y-axis illustrates the average ranging measurement. The P51, P52, P71, and P72 labels denote two different Pixel 5 phones and two different Pixel 7 phones respectively. Data were collected for each combination of parameters over 30 seconds. The dots and whiskers on the graph represent the mean and standard deviation of the measurements.

Several key observations are emerging from the experiment. Firstly, no significant differences were monitored between the two Android apps [3] and [5] when all blue dots and red dots were closely clustered. Secondly, the effect of burst sizes remains unclear when the distance between the access point and the device is insubstantial. Thirdly, the behavior of different phones with similar models is significantly similar when most of the variations are less than 1 meter, except in one case involving the burst size = 8 on Pixel 5 phones. Finally, the offsets are approximately 2400m and 3000m for Pixel 5 and Pixel 7, respectively. Although the lengths of the whiskers are quite similar between Pixel 5 and Pixel 7, the offset of Pixel 7 is notably higher than Pixel 5's. This discrepancy implies a greater deviation in reported measurements of Pixel 7 phones.

4.2.3 Effects of DFS vs. non-DFS. In certain types of access points, such as the Aruba AP-325, the $proc_{time}$ varies for different frequencies due to the type of channels utilized. This discrepancy is particularly notable for frequencies in the

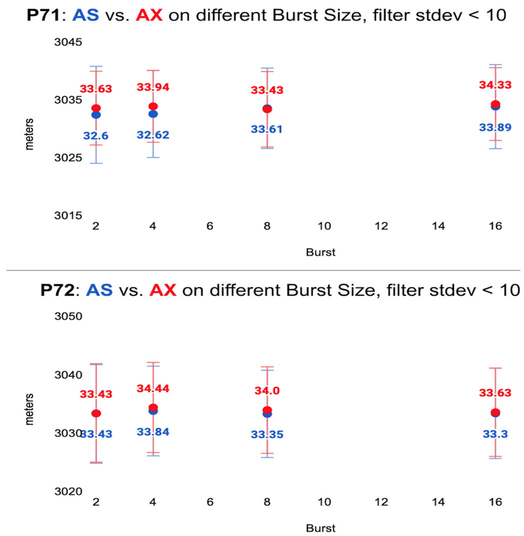

Figure 5: Mean and standard deviation of ranging measurements on various factors of Pixel 7 phone.

Frequency (MHz)	DFS / Non-DFS	Mean Distance (m)
5600	DFS	2447.85
5660	DFS	2446.39
5680	DFS	2446.30
5765	Non-DFS	2735.23
5765	Non-DFS	2737.78
5805	Non-DFS	2733.83

Table 2: DFS vs. Non-DFS in Aruba AP-325.

Dynamic Frequency Selection (DFS) region, which is implemented to prevent commercial chipsets from interfering with military and other reserved communications. Consequently, the disparity between implementing DFS and non-DFS results in differences in the observed distance measurement. For implementing an indoor localization solution, it becomes imperative to account for potential variations in the $proc_{time}$. Table 2 demonstrates significantly distinct $proc_{time}$ between DFS and non-DFS configurations for Aruba AP-325 access points.

However, similar discrepancies are not observed in the Aruba AP-535 access points when the variance of ranging is not significant, as depicted in Table 3. This could be because of differences in the hardware implementation of Wi-Fi chipsets in these newer APs. Nonetheless, given the observed behavior in the AP-325, implementing an indoor localization solution must consider the potential variation in $proc_{time}$ to accommodate all APs, including other AP models and brands exhibiting similar behaviors to the AP-325.

4.3 Is it possible to discern varying distances from the access point?

4.3.1 The capability of one-sided RTT in ranging over long distances. In an endeavor to identify the limits of one-sided RTT in terms of its ranging capabilities, a specialized scenario was devised where a long indoor corridor equipped with an Aruba AP-535 was utilized. Unlike previous experiments outlined in Section 4.1 where the distance ceased at 21 meters, this experiment extended the distance to 42 meters from the designated AP. This setup aimed to create a Line of Sight (LoS) scenario to clarify the limitation of the Aruba AP-535 which was known for providing consistent and reliable ranging results compared to RSSI. Table 4 illustrates that even with increased distance, the performance is better with relatively low error rates than RSSI which reached -80 dBm when the distance is greater than 15 meters. It is noteworthy, however, that the quantity of ranging measurements diminishes as the distance from the AP increases, causing packet loss due to multi-path effects. Furthermore, only a handful of accepted measurements are viable due to the substantial standard deviations of these measurements.

Frequency (MHz)	DFS / Non-DFS	Mean Distance (m)
5280	DFS	2454.84
5500	DFS	2454.62
5500	DFS	2454.51
5200	Non-DFS	2457.66
5200	Non-DFS	2456.94
5220	Non-DFS	2451.79

Table 3: DFS vs. Non-DFS in Aruba AP-535.

Distance (m)	Accepted Measurements	Mean RSSI	Error
0	141/155	-53.99	0.00
6	128/157	-68.09	-5.57
12	135/155	-74.09	-3.41
18	110/146	-82.40	1.09
24	90/143	-88.73	5.48
30	78/148	-88.62	3.33
36	13/121	-93.15	5.24
42	2/50	-102.00	1.35

Table 4: Capabilities in the long-distance measurement of the Aruba AP-535.

In practice, the density of access points commonly deployed in modern infrastructure is high. This suggests the minimal necessity to range to APs located up to 42 meters away since mobile devices are more inclined to connect to the nearest AP. Hence, regarding the implementation of indoor localization, it is more likely for mobile devices to connect to multiple APs within the 15-20 meter distance range. The integration of ranging to multiple different access points can effectively support indoor localization.

4.3.2 Effects of different ground truth distances and burst sizes on error ranging measurements. The objective of this experiment is to examine the influence of various parameters

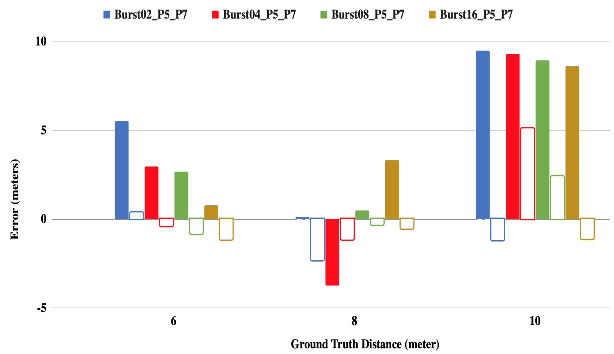

Figure 6: Variations in ranging errors across different ground truth distances, burst sizes, and phone models.

of the WiFiRttScan [3] and WiFiRttScanX [5] Android applications on the ranging accuracy at different ground truth distances. These applications are tested on two Google Pixel 5 and two Google Pixel 7 phones running Android Version 13, enabling the utilization of the one-sided RTT feature with different values of burst sizes (2, 4, 8, and 16).

Figure 6 illustrates the ranging results obtained from varying ground truth distances. Using the measurement at a baseline offset of 4 meters, subsequent measurements at 2-meter intervals were subtracted from this offset to derive error values. The fill and non-fill bars represent Pixel 5 and Pixel 7 phones, respectively, while different burst sizes (2, 4, 8, and 16) are depicted in blue, red, green, and yellow colors, respectively. Several notable observations can be made from the figure: (1) With some minor exceptions, larger burst sizes tend to yield more accurate measurements as the ground truth distance increases. Generally, a pattern of decreasing errors from burst sizes 2 to 16 is observed. (2) Pixel 7 errors appear more accurate than Pixel 5, as the non-fill bars are generally lower than the fill bars.

5 CONCLUSION

Based on the data analysis and results discussed in section 4, it becomes evident that the utilization of one-sided RTT holds promising results for indoor localization. Not only is RTT capable of measuring various distances, but it can also operate at distances over 20 meters to access points, which is challenging with RSSI. The application of one-sided RTT could be widely adopted for many types of access points without the requirement of 802.11mc implementation. However, $proc_{time}$is a factor that should be carefully considered as the turnaround time is unknown compared to two-sided RTT. As the results indicated in the experiment of sections 4.2 and 4.3, $proc_{time}$may depend on the type of APs, phone models, and burst sizes. However, a favorable aspect is that $proc_{time}$does not alter too rapidly and may remain stable over a short period. Combining one-sided RTT with IMU sensors such as accelerometers and gyroscopes can help eliminate the constant offset caused by $proc_{time}$and perform indoor localization efficiently.

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