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WiFi round-trip time (RTT) fingerprinting: an analysis of the properties and the performance in non-line-of-sight environments

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ABSTRACT

Indoor positioning systems based on WiFi round-trip time (RTT) measurement were reported to deliver sub-metre-level accuracy using trilateration, under ideal indoor conditions. However, the performance of WiFi RTT positioning in complex, non-line-of-sight environment remains an open research question. To this end, this article investigates the properties of WiFi RTT in several real-world indoor environments on heterogeneous smartphones. We present three datasets collected on a large-scale building floor, an office room and an apartment. The datasets contain both RTT and received signal strength (RSS) signal measures with correct ground-truth labels for further research. Our results indicated that in a complex indoor environment, RTT fingerprinting system delivered an accuracy of 0.6 m which was 107% better than traditional RSS fingerprinting and 6 m better than RTT trilateration which failed to deliver sub-metre accuracy as claimed.

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Indoor Positioning; wiFi round-trip time; non-line-of-sight

1. Introduction

Traditional GNSS systems (such as GPS) are indispensable for outdoor positioning and navigation (Gondelach and Linares 2021; Zhang and Masoud 2020). However, indoor environments remain a challenge for such technology. The thick concrete walls and complex interiors of modern buildings create a blockage and greatly attenuate the GPS signals. Therefore, fine-grained indoor positioning tracking remains a research challenge.

Since the release of the WiFi IEEE 802.11–2016 standard (Committee et al. 2009)), WiFi fine-timing measurement (FTM) protocol has been a competitive signal feature for WiFi-based indoor positioning. RTT is an estimate of the distance between an initiating station (e.g. a smartphone)

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and a responding station (e.g. a WiFi access point (AP)), which offers a more accurate distance measure for trilateration and avoids the hassle of constructing and maintaining the fingerprinting database (Feng, Nguyen, and Luo 2022b; Xue et al. 2020). However, despite its promise in achieving sub-metre positioning accuracy in ideal line-of-sight (LoS) conditions (Feng, Nguyen, and Luo 2022a; Zhang et al. 2020), the performance of WiFi RTT in real-world complex, non-LoS (NLoS) indoor environments remained unexplored.

Therefore, this article will perform a thorough investigation of the properties of the WiFi RTT signal in large, complex, and realistic NLoS indoor experiments that include an office, an apartment, a corridor, and a campus floor on different smartphones. We also assess the positioning accuracy of WiFi RTT, RSS, hybrid RTT-RSS fingerprinting, and trilateration systems in the above challenging environments.

1.1. The article's contributions

The article's contributions are summarised as follows:

- **Three real-world WiFi RTT & RSS datasets with ground truth labels, including one collected in a large-scale building floor testbed**. To support the development of future RTT positioning systems, we contribute three datasets containing both WiFi RTT and RSS signal measures with ground truth labels manually verified by multiple human testers. To the best of our knowledge, these were the first publicly available datasets that contain both WiFi RSS and RTT signal measures, as well as LoS conditions of each AP for every location.
- **Thorough WiFi RTT analysis in challenging NLoS indoor environments**. We analysed the most relevant WiFi RTT signal properties on three smartphones to investigate the true nature of the measurement. We also considered challenging scenarios such as AP interference, body blockage, wall attenuation, reflections, and so on. The impacts of different placements and orientations of smartphones were also analysed.
- **Performance ranking of WiFi RTT, RSS, hybrid RTT-RSS fingerprinting, and trilateration in various real-world scenarios**. We conducted a comparative analysis on RTT- and RSS-based indoor fingerprinting systems with different Machine Learning algorithms and trilateration.

The rest of the article is organised as follows. Section 2 introduces the related work in WiFi RTT indoor positioning. Section 3 provides a detailed description of WiFi RTT technology, then the properties of WiFi RTT signal measure in challenging environments are investigated in Section 4. The experimental setup and empirical performance of WiFi RTT fingerprinting are presented and analysed in Section 5. Finally, Section 6 concludes our work and outlines future work.

2. Related work

To achieve robust and reliable indoor positioning performance, systems utilising easily-employed signal transmitters and receivers were proposed. Technologies such as Ultra-wideband (UWB) (Poulose and Han 2020; Ridolfi et al. 2021), Bluetooth Low Energy (BLE) (Bai et al. 2020; Spachos and Plataniotis 2020), Ultrasonic (Carotenuto et al. 2020; Lindo et al. 2015) and LED (Hassan et al. 2015; Rahman, Haque, and Kim 2011) were leveraged in the literature for indoor tracking. Due to the omnipresent infrastructure of WiFi-enabled devices, WiFi fingerprinting has become one of the most popular approaches for indoor positioning (Liu et al. 2020; Xue et al. 2020). Such systems used the WiFi received signal strength (RSS) as signal features, and were known to achieve an accuracy of a few metres on average (Abbas et al. 2019; Poulose, Kim, and Han 2019).

Systems that leverage WiFi RTT were reported to achieve sub-metre accuracy indoors (Dümbgen et al. 2019; Gentner et al. 2020). Many have conducted research to verify the accuracy of the systems based on WiFi RTT with different positioning algorithms, including trilateration (Choi and Choi 2020), traditional machine learning (Hashem, Harras, and Youssef 2021), and deep learning (Seong et al. 2021). However, the challenges for RTT and RSS in NLoS environments were also highlighted in (Nguyen et al. 2021; Singh, Choe, and Punmiya 2021). To make the best of WiFi signals and achieve better positioning accuracy, systems supporting both WiFi RTT and RSS measurements were proposed in (Dong, Arslan, and Yang 2021; Hashem, Harras, and Youssef 2021). Furthermore, systems were proposed to identify LoS scenarios in order to gain a promising positioning result (Cao et al. 2020; Sun et al. 2020). Some have further studied some general properties of WiFi RTT and discovered an offset in RTT measurements (Gentner et al. 2020; Horn 2020). The biases of such offset in different devices (Choi and Choi 2020; Choi, Choi, and Talwar 2019) and in different distances (Sun et al. 2020) were also analysed. Different calibration models were leveraged to compensate for such offset: fixed offset (López-Pastor et al. 2021), double exponential (Horn 2020), linear polynomial, and quadratic polynomial (Choi and Choi 2020). However, to the best of our knowledge, there is still a lack of comprehensive analysis of WiFi RTT measurements in challenging environments.

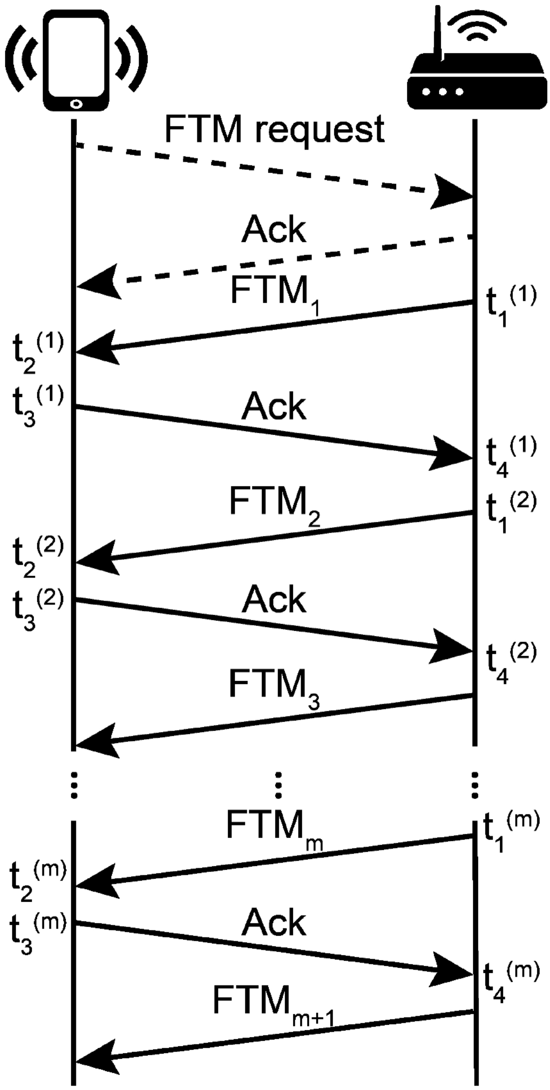


Figure 1. Overview of FTM (also known as RTT) protocol. The dashed lines show the control messages before the measurement took place.

3. RTT background

This section overviews the underlying mechanism of WiFi RTT technology and provides in-depth description of the working principle of RTT trilateration and RTT-based fingerprinting.

3.1. RTT protocol

WiFi RTT is a handshaking FTM protocol standardised by IEEE 802.11–2016 to estimate the distance between an initiating station (e.g. a smartphone) and a responding station (e.g. a WiFi AP), using round trip time measurements. As shown in Figure 1, an RTT measurement starts with an FTM request sent by the smartphone to the AP. The AP will then respond with an acknowledgement (Ack) message indicating whether it agrees with the request. Once agreed, the AP will send an FTM message FTM_1 to the smartphone at time $t_1^{(1)}$. After receiving the FTM_1 message at time $t_2^{(1)}$, the smartphone will send another acknowledgement (Ack) at time $t_3^{(1)}$ to the AP, that arrives at the time $t_4^{(1)}$. The timestamps of the process will be stored and transmitted back to the smartphone through the following FTM_2 message. The WiFi RTT measurement is defined as:

$$RTT = \frac{1}{m}\sum_{i=1}^{m}((t_4^{(i)} - t_1^{(i)}) - (t_3^{(i)} - t_2^{(i)})) \tag{1}$$

where m is the total number of FTM round trips, $(t_4^{(i)} - t_1^{(i)})$ is the time it takes for the ith round trip, $(t_3^{(i)} - t_2^{(i)})$ is the time delay inside the smartphone. The distance is then calculated as:

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

where c is the speed of light.

On Android phones, each measuring burst contains eight RTT measures and their average is recorded as the final RTT measure to represent the distance estimation. Note that the whole process does not require any direct connection between the AP and the smartphone.

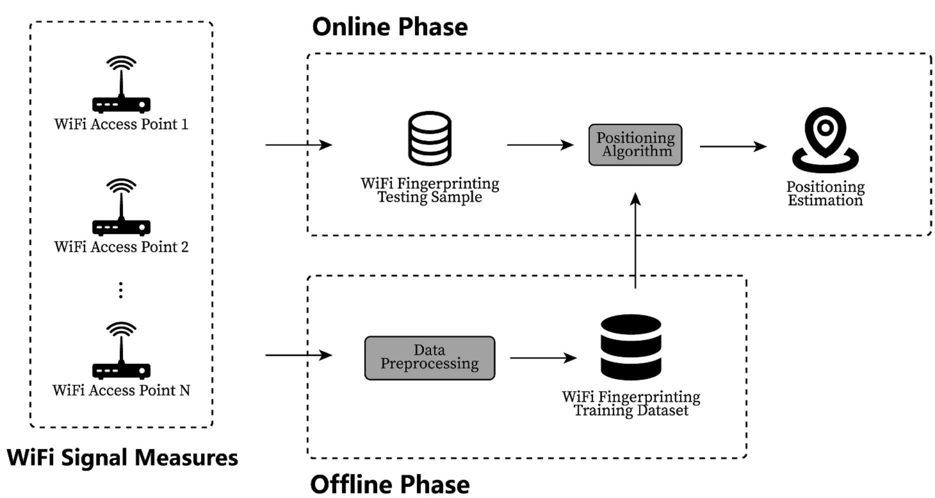


Figure 2. Overview of WiFi-based fingerprinting for indoor positioning.

3.2. RTT-based fingerprinting

Being susceptible to interior changes of the indoor environment, WiFi signal measures may vary greatly in two locations close to each other. Especially for NLoS scenarios, where WiFi propagation suffers from blockage, reflection, attenuation, etc., the signal measures would fluctuate and become unreliable. Thus, in a complicated indoor space, each location will have its own unique WiFi signal measurements. Such unique measurements are defined as the WiFi fingerprint of a specific location and could be used for indoor positioning.

As shown in Figure 2, the fingerprinting approach normally consists of an offline phase and an online phase. In the offline phase, a database containing the unique WiFi fingerprints, along with the ground-truth coordinates of all reference points in the testbed, is collected. Then, a data preprocessing method is applied to replace missing values, remove duplicates and outliers, and normalise the collected signal measures. Next, this dataset is used to train a positioning algorithm. In the online phase, when a user walks into the testbed for the first time, a new WiFi sample is reported to the positioning system. After the same preprocessing process, the testing sample is compared with the training samples in the offline database. Finally, the positioning algorithm makes the positioning estimation. Though fingerprinting is widely used by RSS-based indoor positioning systems, it could also be utilised by RTT signal measure.

RTT leverages the time the WiFi signal travels from the transmitter to the receiver to obtain the distance in between. Because WiFi signal travels at the speed of light, any minor delays in the propagation path would lead to a noticeable change in the RTT signal measurement. Thus, RTT measures can also be used to represent the characteristics of WiFi signal propagation. Intuitively, just like RSS fingerprints, different locations in the same testbed would also have their unique RTT fingerprints. Compared to RSS, RTT is more sensitive to interior changes and is believed to deliver more promising fingerprinting performance than RSS.

3.3. Trilateration

RTT signal measurement was first introduced to obtain the distance between the AP and the user directly. Leveraging the distances between the user and multiple APs, the positioning system could simply determine the user's location by trilateration. Trilateration is a geometric method using both the known locations of several APs and the distances between each AP and the user to perform localisation. Figure 3 illustrates how WiFi RTT measures are incorporated into trilateration to locate the user.

In a two dimensional space, at least three intersecting circles located at known locations are required to determine the user's location, defined as:

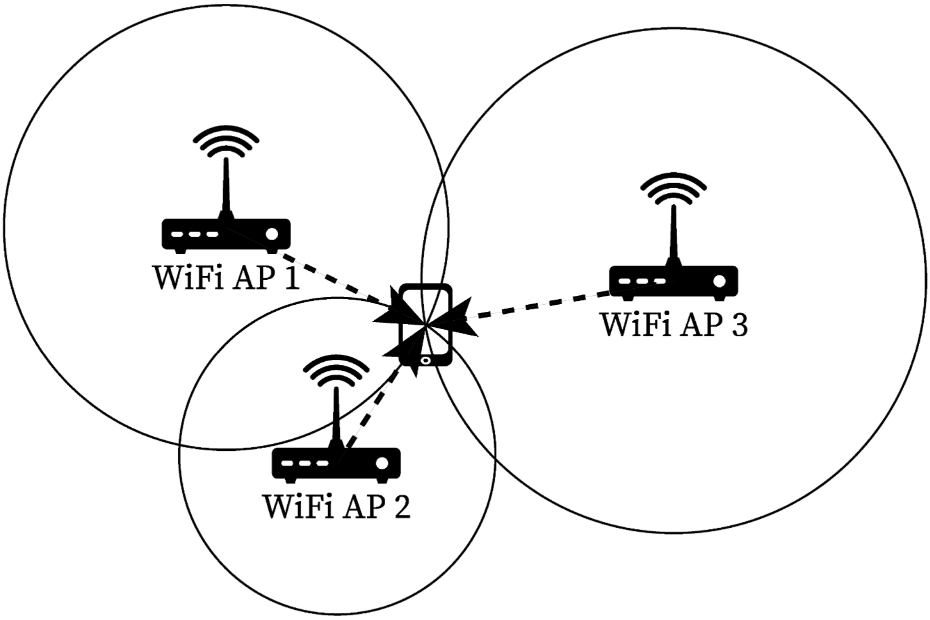


Figure 3. Overview of RTT-based trilateration in a two-dimensional space.

$$(long - long_1)^2 + (lat - lat_1)^2 = dist_1^2 \tag{3}$$

$$(long - long_2)^2 + (lat - lat_2)^2 = dist_2^2 \tag{4}$$

$$(long - long_3)^2 + (lat - lat_3)^2 = dist_3^2 \tag{5}$$

Furthermore, in 3-D positioning space, the equations are formulated as:

$$(long - long_1)^2 + (lat - lat_1)^2 = dist_1^2 \tag{6}$$

$$(long - long_2)^2 + (lat - lat_2)^2 = dist_2^2 \tag{7}$$

$$(long - long_3)^2 + (lat - lat_3)^2 = dist_3^2 \tag{8}$$

$$(long - long_4)^2 + (lat - lat_4)^2 = dist_4^2, \tag{9}$$

where *long* and *lat* are the coordinates of the user to be solved, $(long_1, lat_1)$, $(long_2, lat_2)$, $(long_3, lat_3)$,$(long_4, lat_4)$ represent the true coordinates of the know APs in the testbed, and $dist_1$, $dist_2$, $dist_3$, $dist_4$ are the distances between the user and the APs derived from RTT measurement.

Compared to RTT fingerprinting, trilateration method does not need the data preparation and maintenance process to collect and update the training data over a long period of time. Besides, RTT measurement can take place without direct connections to the APs, which ensures the user's privacy. Knowing only

Table 1. The smartphones used in the experiments.

Name	Year manufactured	Operating system	CPU chipset	WiFi standards
Google Pixel 3	2018	Android 9	Qualcomm Snapdragon 845	802.11ad multi-gigabit, 802.11ac 2x2, 802.11k/r/v
LG G8X ThinQ	2019	Android 11	Qualcomm Snapdragon 855	802.11ax-ready, 802.11ac Wave 2, 802.11a/b/g, 802.11n
Nokia 8.5 5G	2020	Android 11	Qualcomm Snapdragon 765G 5G	802.11ax-ready, 802.11ac Wave 2, 802.11a/b/g, 802.11n

the exact locations of APs, the user could easily obtain the localisation of the current position by leveraging trilateration. However, RTT trilateration highly relies on the LoS condition. On the contrary, RTT fingerprinting could utilise the unique measurement caused by NLoS to better localise the user.

4. Analysis of the RTT properties

This section details the analysis of the WiFi RTT measures, in comparison to RSS, in a complex office environment, filled with furniture, electrical devices and electromagnetic signal transmitters (e.g. WiFi, BLE), one of the most common indoor environments for WiFi-based indoor positioning. The RTT-enabled smartphones used in this analysis were LG G8X ThinQ (LG), Google Pixel 3 (Pixel), and Nokia 8.5 5 G (Nokia) (see Table 1). The Google WiFi router was used as the Access Point for the experiments. We recorded 300 WiFi samples per reference point. Note that at the time of writing, most iOS devices did not support IEEE 802.11–2016 standard. Additionally, there was no iOS API to access WiFi RTT distance measure or location. Therefore, we only focused on WiFi RTT experiments on Android phones.

4.1. Body blockage and AP interference

In order to observe the stability of the RTT and RSS signal, we recorded the measures in three different situations, including LoS, body blockage and AP interference, as follows:

- To create the LoS condition, we set the smartphone 3 m away from the AP with no obstacles in-between, while keeping both of them at the same height to minimise potential interference.
- To create body blockage, a person stood 20 cm right next to the smartphone, to imitate the scenario where the user accidentally blocks the signal transmission.
- To observe the influence of AP interference, we introduced two more Google APs in the environment. Furthermore, we put the phone inside a plastic case.

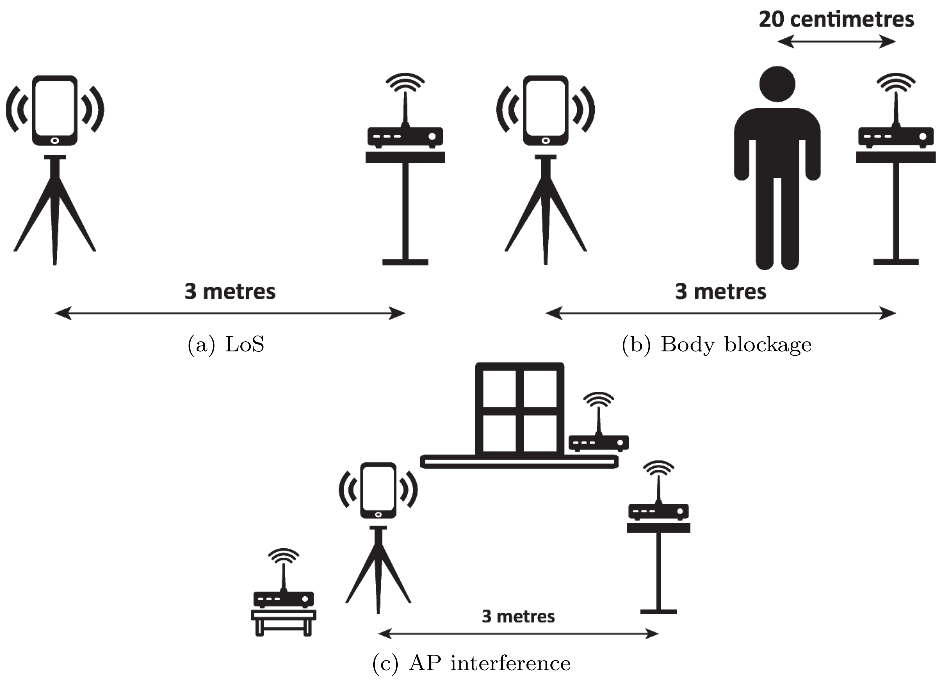


Figure 4. The settings of LoS, AP interference, body blockage scenarios.

The settings of the three situations are shown as Figure 4.

Figure 5 demonstrates that in the LoS scenario, LG and Nokia had more stable RSS measurements. LG had stronger signals than the other two. We observed that both Pixel and Nokia phones were more vulnerable with the AP interference and that they had weaker and less stable RSS measures. The influence of the human body as an obstacle was noticeable. Not only would the RSS measures be unstable, but the signal strength would also be reduced drastically. It was also observed that the plastic phone case only had a negligible impact on the RSS measures (see Figure 6). Thus, the phone case condition will not be considered further.

The results from the RTT measurement are shown in Figure 7. We observed that in the LoS scenario, LG had the most stable RTT measure, while Pixel had the worst measures which is consistent with their RSS performances. It was also observed that each smartphone had its own RTT offset due to the impact of the complex indoor environment, which was consistent with previously reported research (Gentner et al. 2020; Guo et al. 2019). Nokia had the most surprising offset of more than 6.5 m. Under the AP interference, LG and Nokia were more robust than Pixel, and RTT measures were more stable than RSS measures. When the human body blocked the signals, all three smartphones generated larger RTT measures (see Figure 8).

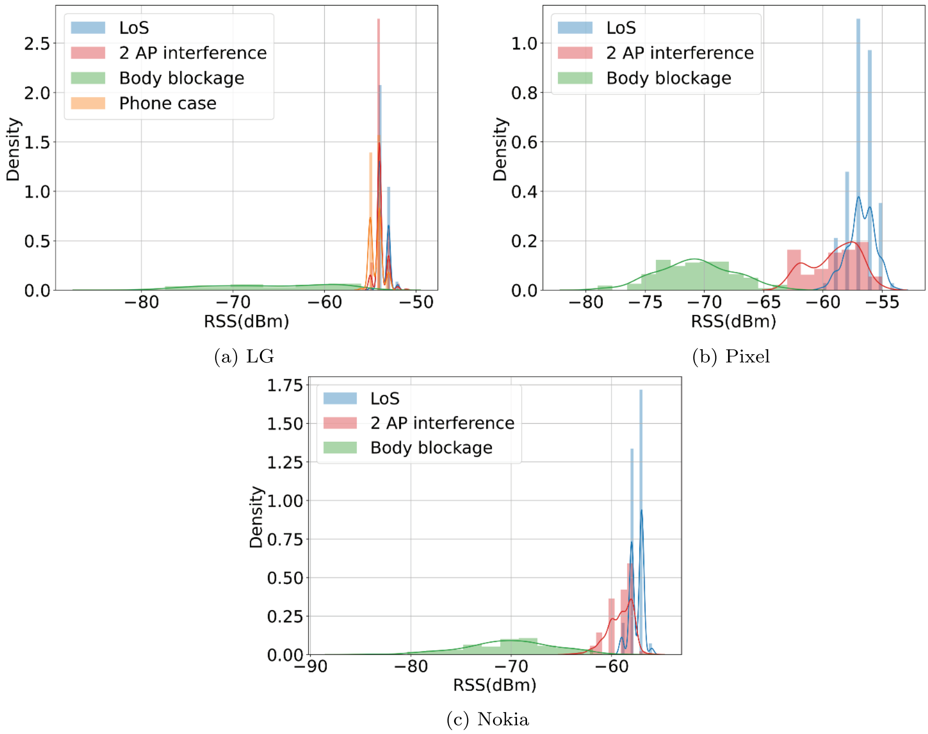


Figure 5. The WiFi RSS data distribution under LoS, AP interference, body blockage and phone case blockage (only LG) scenarios. The smartphones were set 3 m away from the Google WiFi AP.

4.2. Placement and orientation

To further investigate the influences caused by different placements and orientations of the smartphone, we performed the following experiments.

First, we evaluated the RTT and RSS distributions when the smartphone was held in different ways. In this scenario, the smartphone was placed 2 m away with a clear LoS and at the same height as the AP. Then, we introduced different scenarios to place the smartphone (see Table 2). The distributions of RTT and RSS are shown in Figure 9. The variance of the RSS measure could be up to −20 dBm and that on RTT could be up to 0.65 m. In general, RTT was more sensitive to the phone placement as it travels at the speed of light and any minor delay would cause a considerable estimation error.

Next, we changed the heading directions of the phone and took the corresponding RTT measures (see Figure 10). The results demonstrated significant influences on the RTT measure with LG and Nokia which both produced an offset of up to 0.4 m.

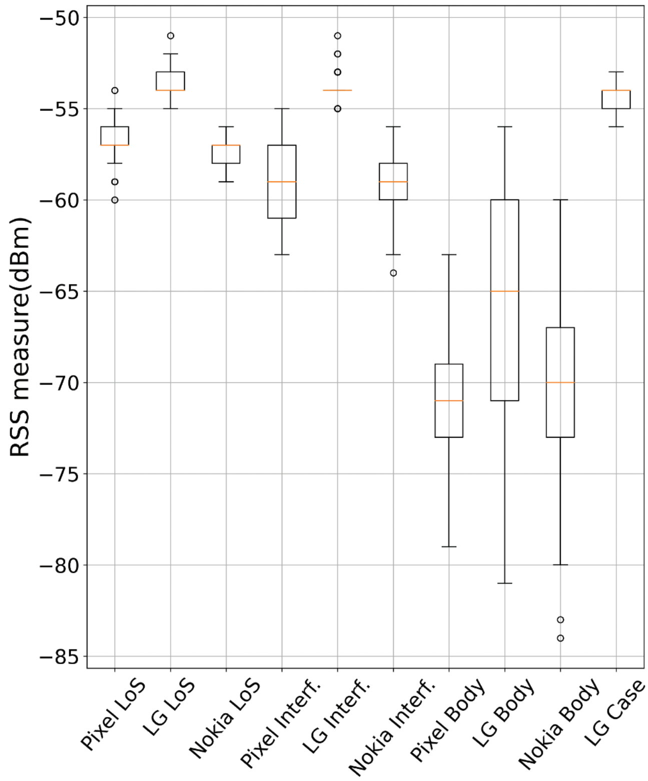


Figure 6. The comparison of RSS distribution under LoS, AP interference, body blockage and phone case blockage on three smartphones. Longer bar indicates signal instability.

4.3. Large scale variation

4.3.1. Horizontal ranging

To study the horizontal spatial impact on the signal measurements, we performed ranging experiments under three different environments as shown in Figure 11. They were office LoS, office NLoS and corridor LoS. The length of the testing area of these three ranging tests was 3 m, 2 m, and 10 m, respectively. The smartphone was moved across the testing area away from the AP at 20 cm intervals. To construct an NLoS testbed, we set the AP at one side of a 16 cm thick wall while recording the WiFi measurements on the other side. In all these tests, the smartphone was set at the same height as the AP to only focus on horizontal ranging. We recorded the WiFi signals for 30 seconds per reference point.

The ranging test results showed that within 10 metres, the RTT measure would have some constant offset from the true distance, which may be caused by the signal attenuation (see Figures 12-14). Such offset varies from one smartphone to another, which is consistent with our findings in the previous section about body blockage and AP interference. The NLoS

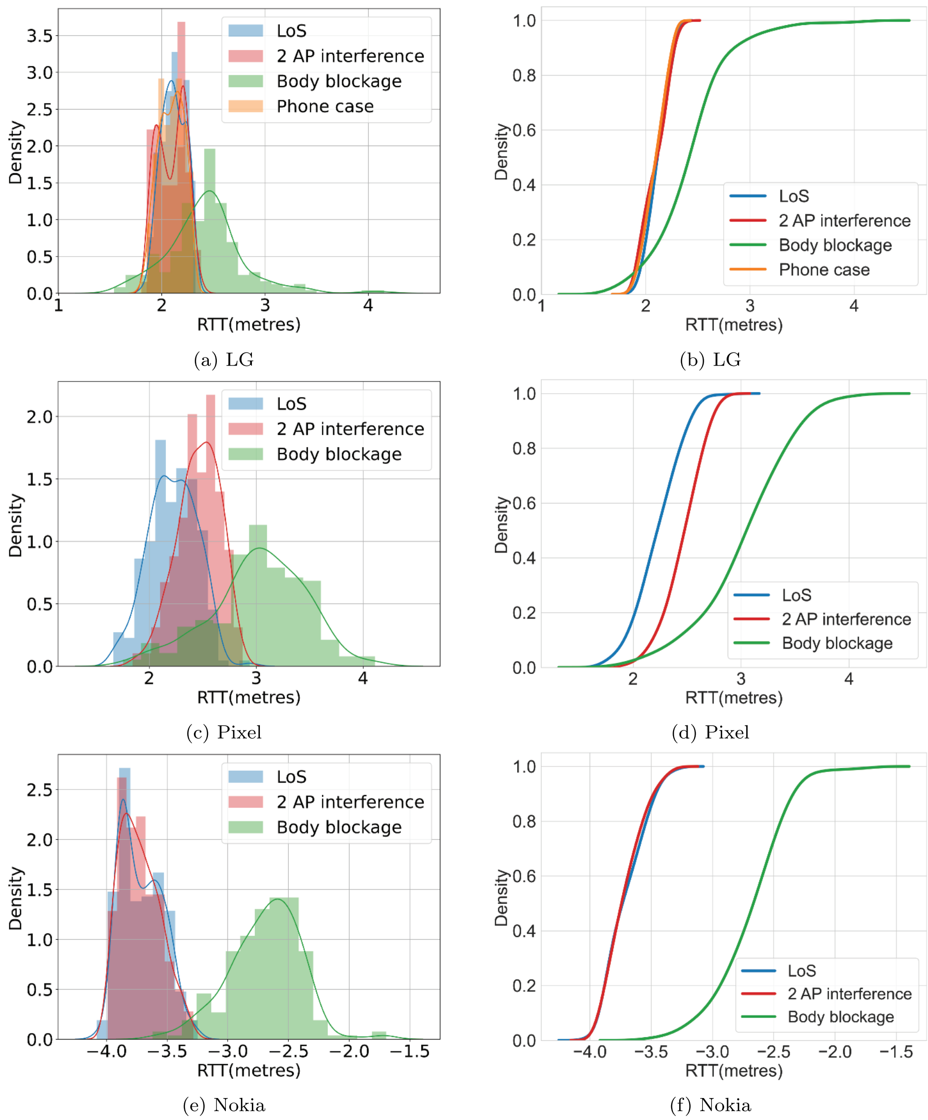


Figure 7. The raw WiFi RTT data distribution and CDF plot under LoS, AP interference, body blockage and phone case blockage (only LG) scenarios. The smartphones were set 3 metres away from the Google WiFi AP.

condition also affects the constant offset pattern of the RTT measures (see Figure 12 and Figure 13). In the corridor, where the signals suffered from much more reflections, RSS measure becomes unpredictable as shown in Figure 14. It was surprising that locations 5 m or 8 m away had the same RSS measure. It may be concluded that the RTT measures were more robust and showed a clear positive correlation to the true horizontal distance, compared to RSS measures.

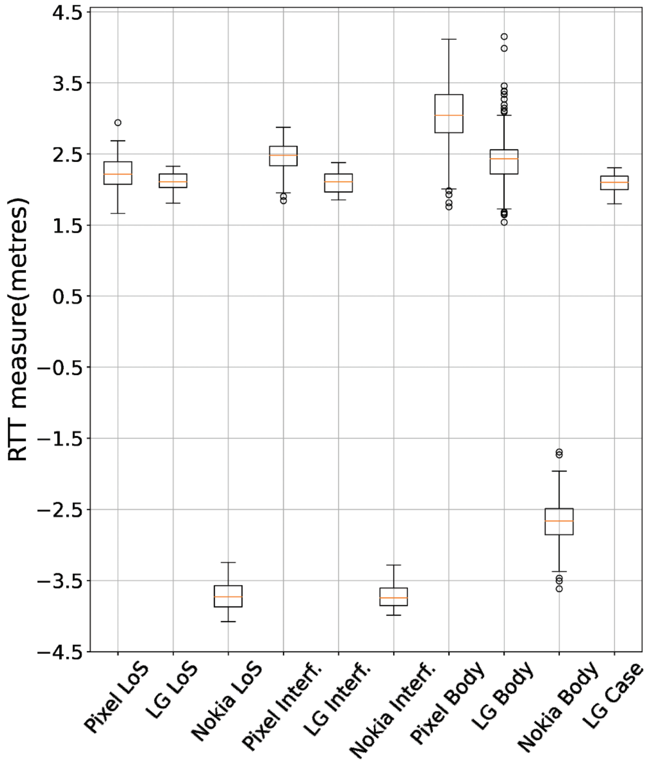


Figure 8. The comparison of RTT distribution under LoS, AP interference, body blockage and phone case blockage on three smartphones. Longer bar indicates signal instability.

Table 2. The different placements of the smartphone.

Placement	Description
LoS	The back of the phone faces towards the AP and is at the same height.
NLoS	A 16 cm thick wall blocks the signal.
Face to	The back of the phone faces directly to the AP.
Face back	The screen of the phone faces directly to the AP.
Face up	The screen of the phone points to the ceiling.
Face down	The screen of the phone points to to the floor.
Set high	The phone is held higher than the AP.
Set low	The phone is held lower than the AP.

4.3.2. Vertical ranging

To evaluate the vertical spatial impact on the signal measurements, we performed ranging experiments. To focus on the vertical distance, the testbed was a completely LoS scenario. The smartphone was placed directly above the AP and moved further away from it. As shown in Figure 15, the RTT vertical ranging had an offset that varied among different smartphones, which was consistent with the horizontal ranging results. For LG and Pixel, the RTT measures showed a clear positive correlation to the true horizontal distance. But the RTT measures from Nokia barely reflected the changes in vertical distance. It was observed

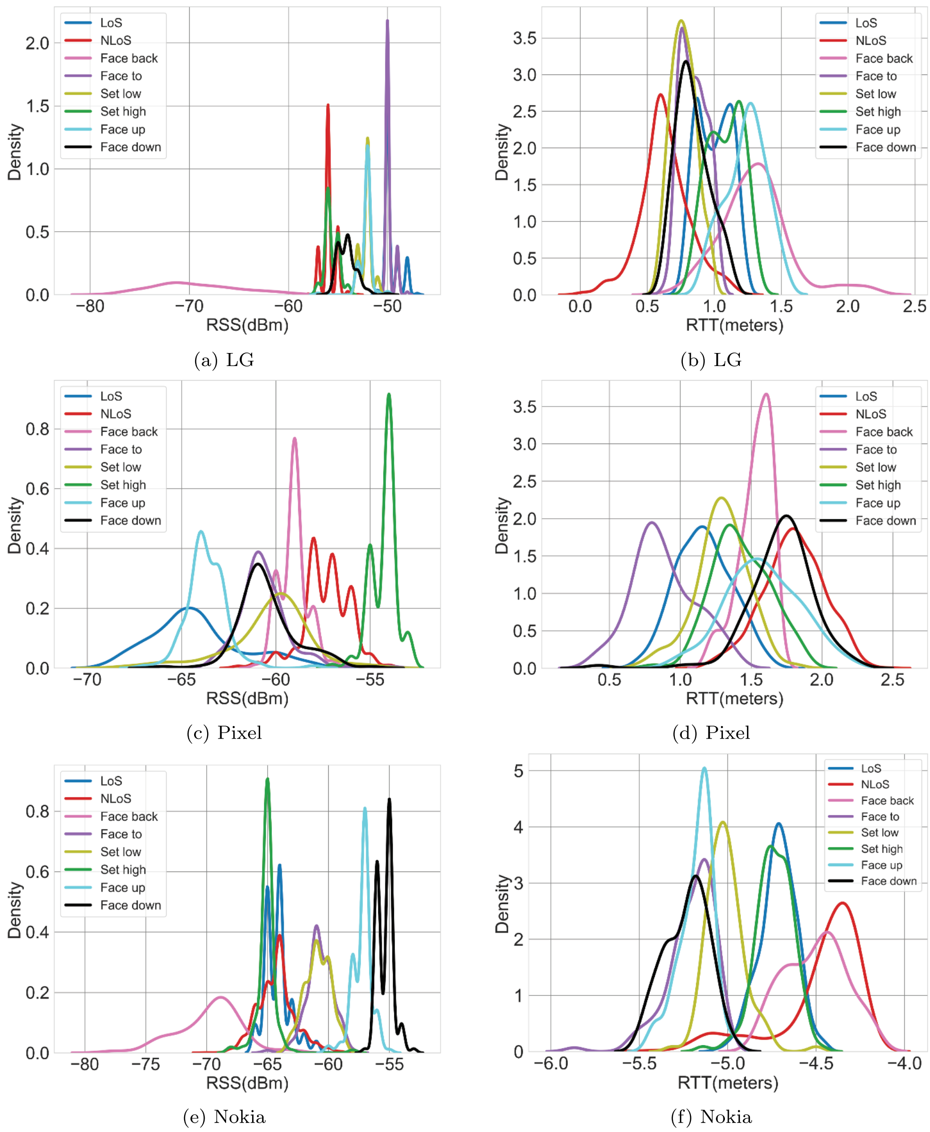
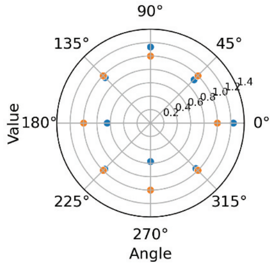


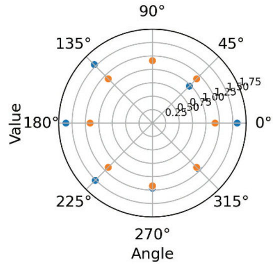
Figure 9. The WiFi RTT and RSS distributions with different gestures as described in Table 2. The smartphones were set 2 m away from the AP.

that in LoS vertical ranging experiment, the RSS signal measures were less robust than RTT measures, especially for Pixel and Nokia.

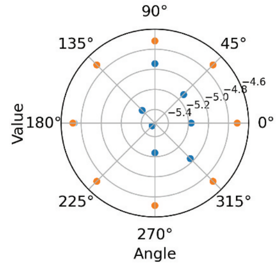
Based on both the horizontal and vertical ranging experiments, we observed a positive correlation between WiFi RTT measures and horizontal and vertical distances. Moreover, the instability of RTT measures in different scenarios ensured the unique WiFi fingerprints of different locations. As discussed in Sections 3.2 and 3.3, to obtain the three-dimensional coordinates of the user's location, fingerprinting and trilateration methods could both be utilised. To perform fingerprinting in 3-D space,



(a) LG

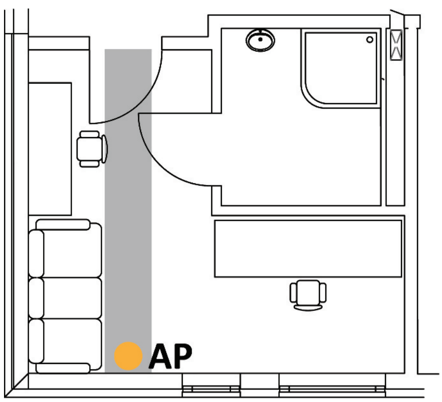


(b) Pixel

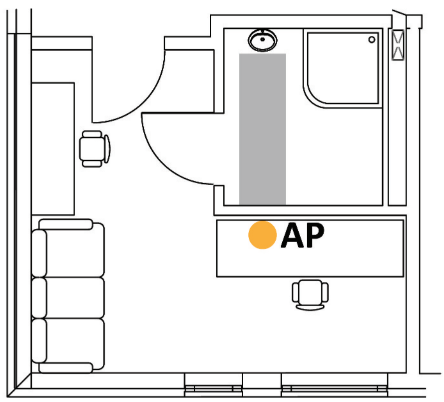


(c) Nokia

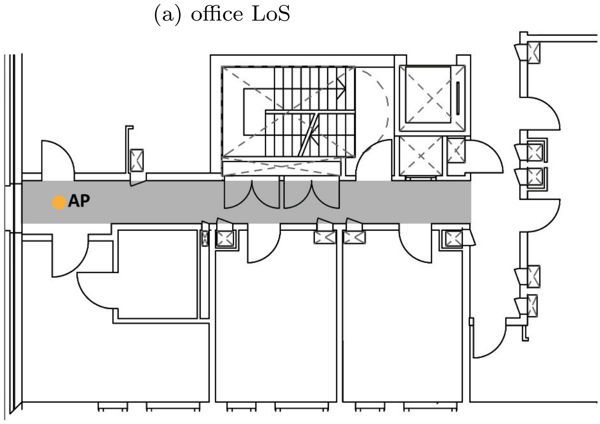
Figure 10. The WiFi RTT distribution of the smartphone with different heading directions. The smartphone was set 2 m away and at the same height as the AP with its screen pointing to the ceiling. The orange dots indicate the average LoS RTT measures while the phone is in the LoS scenario.



(a) office LoS



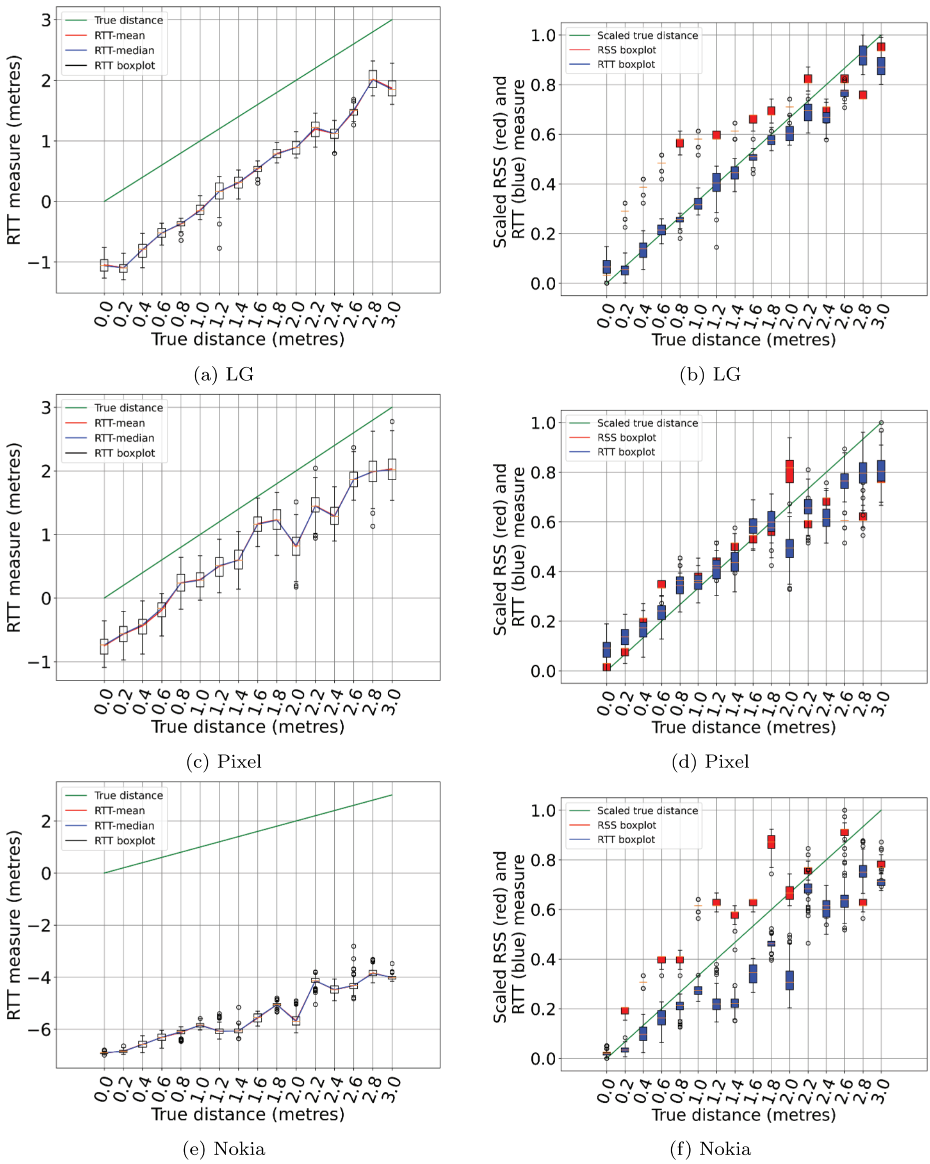
(b) office NLoS



(c) corridor LoS

(d) an actual photo of the corridor

Figure 11. Overview of the ranging testbeds. The orange dots indicate the location of the AP. The grey area shows the experimental area.



(a) LG (b) LG

(c) Pixel (d) Pixel

(e) Nokia (f) Nokia

Figure 12. RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in office LoS scenario. The data was pre-processed, so all of its values are between 0 and 1. Boxplots of RSS measures are in red while those of RTT are in blue. The bigger the scaled RSS is, the weaker the signal is.

a 3-D dataset needs to be collected in the offline phase and fed into a positioning algorithm. As the WiFi RSS and RTT measures vary in both horizontal and vertical directions, the unique fingerprints of a 3-D location could be used to locate the user. Furthermore, as illustrated in Section 3.3, at least 4 APs with known locations are required to locate the user's location by trilateration.

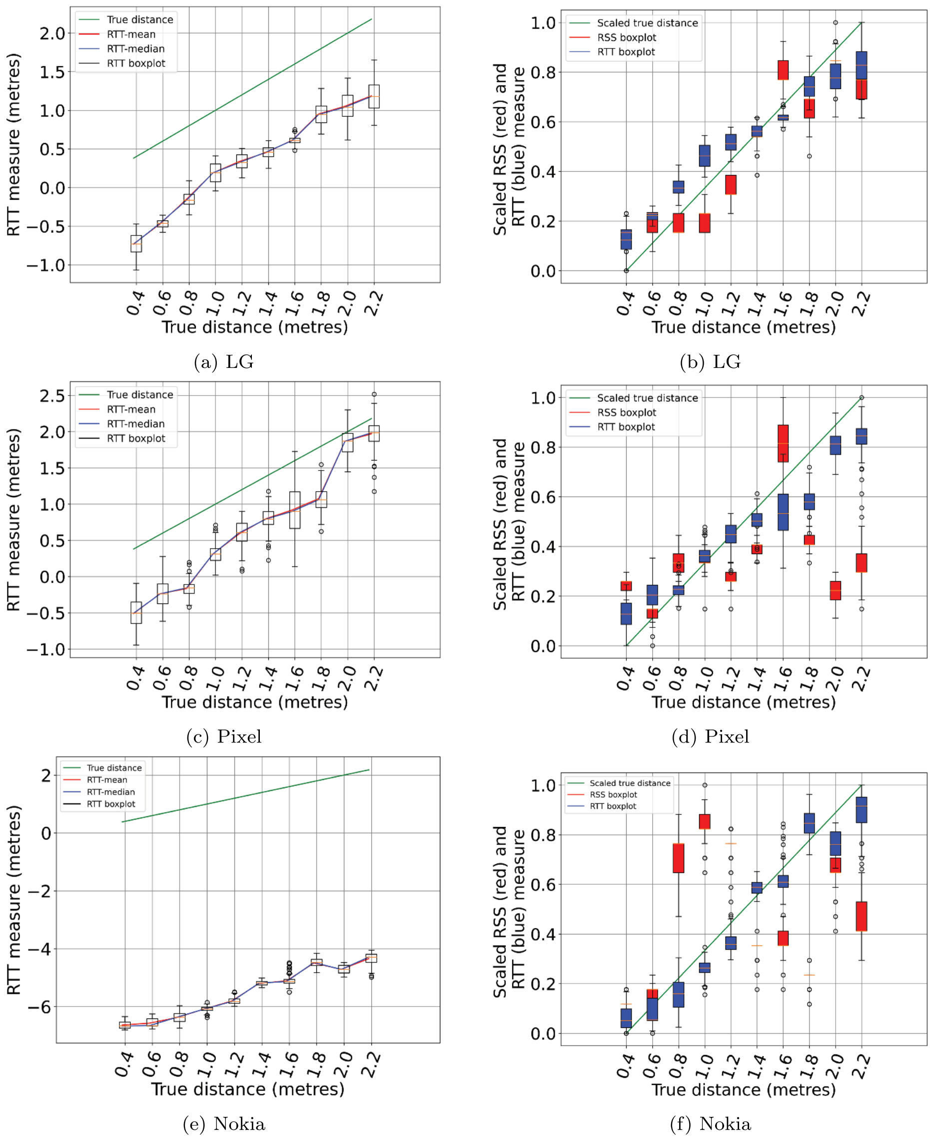
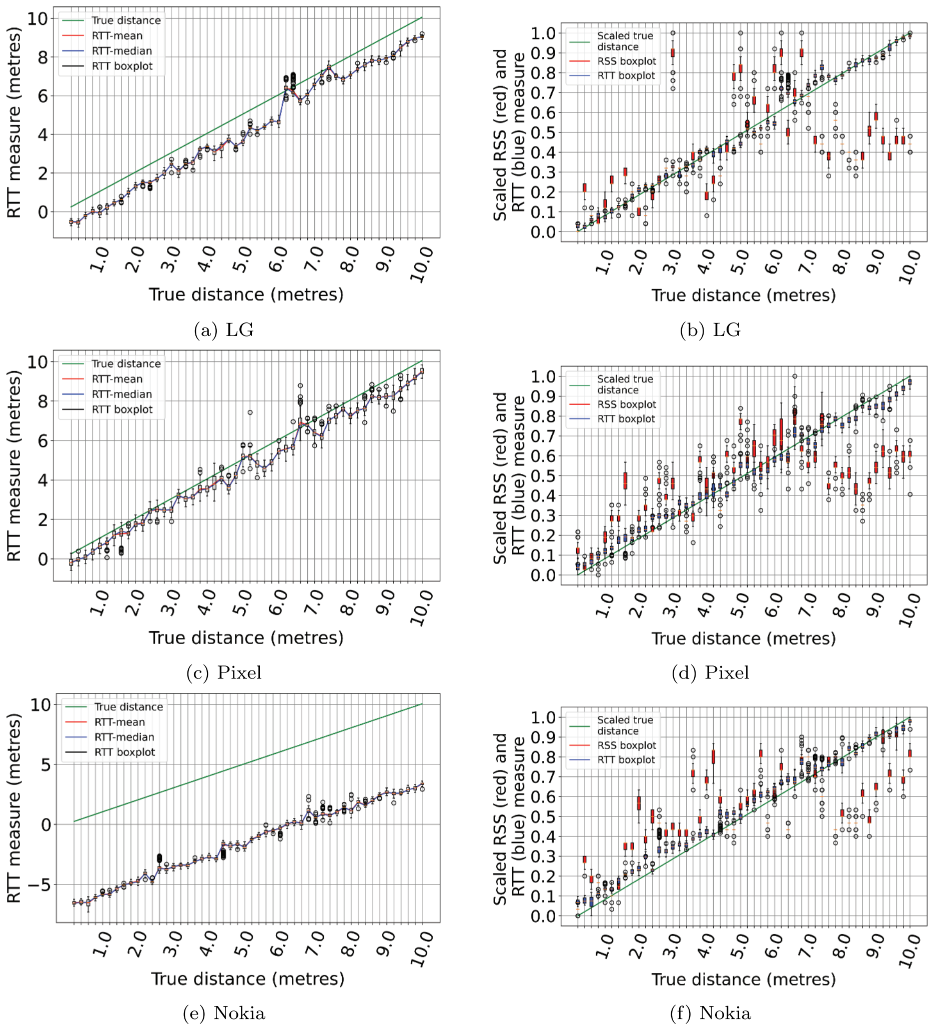


Figure 13. RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in office NLoS scenario. Boxplots of RSS measures are in red while those of RTT are in blue. The bigger the scaled RSS is, the weaker the signal is.

4.4. Summary of signal properties

Table 3 summarises the properties of RTT and RSS. In short, RTT measures were more stable and more reliable than RSS measures in most situations. Furthermore, RTT measures had an offset in ranging which should be taken into consideration. The robustness towards interior changes makes RTT a better measure to leverage for indoor positioning fingerprinting.

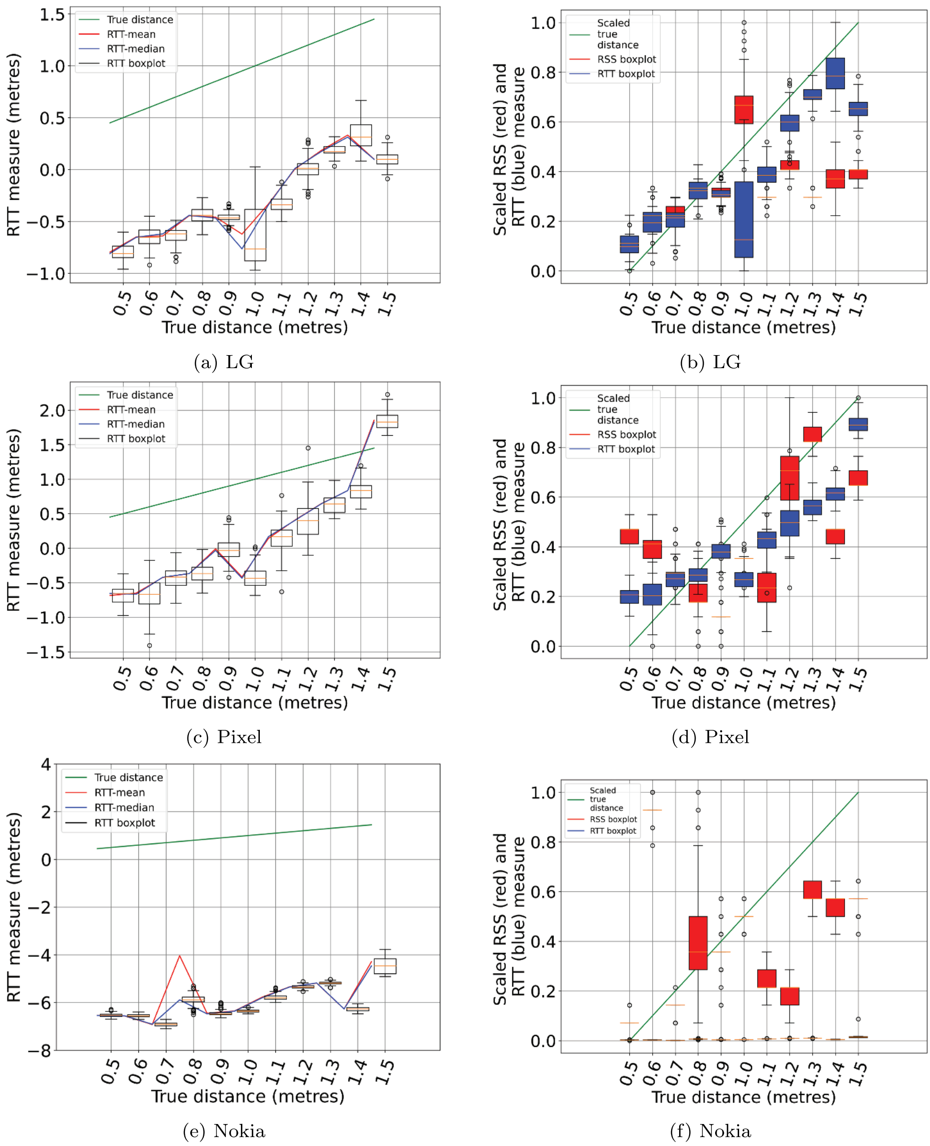


(a) LG (b) LG (c) Pixel (d) Pixel (e) Nokia (f) Nokia

Figure 14. RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in corridor LoS scenario. Boxplots of RSS measures are in red while those of RTT are in blue. Note that the bigger the scaled RSS is, the weaker the signal is.

5. RTT indoor fingerprinting

To validate the performance of WiFi RTT-based indoor positioning system, we performed experiments in three real-world environments including an entire floor of a campus building, an office room, and an apartment. The performance of WiFi RSS-based indoor positioning, measured at the same training locations, was used as the baseline.



(a) LG (b) LG (c) Pixel (d) Pixel (e) Nokia (f) Nokia

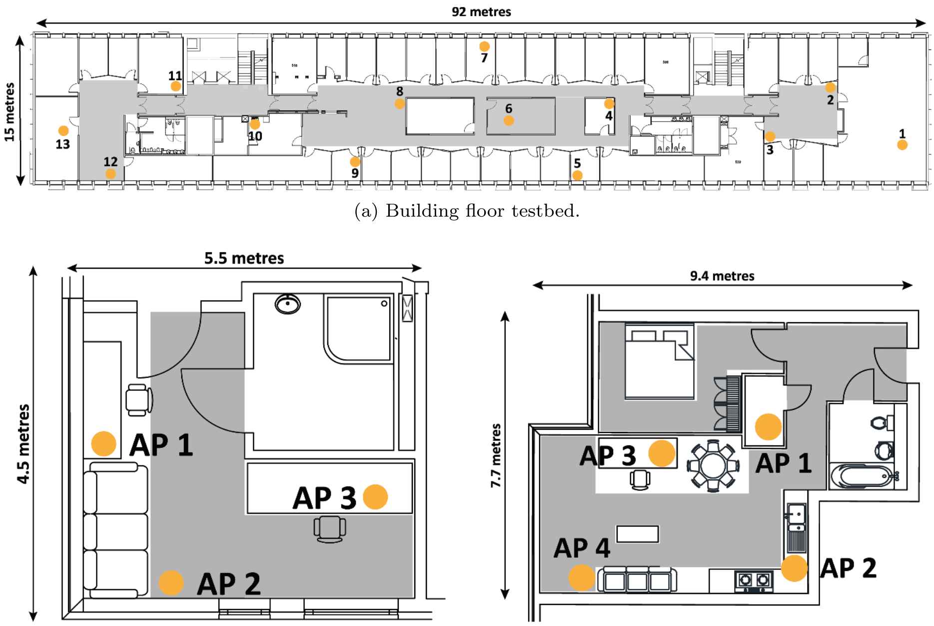
Figure 15. RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in vertical ranging experiment. Boxplots of RSS measures are in red while those of RTT are in blue. Note that the bigger the scaled RSS is, the weaker the signal is. For Nokia phone, the RTT measures barely changed when the phone was moved, leading to a barely visible boxplot.

5.1. Experimental setup and data collection

We present three datasets: a campus building floor, an office, and an apartment (https://github.com/Fx386483710/WiFi-RTT-RSS-dataset) (see Figure 16). To the best of our knowledge, the proposed datasets were the first publicly available large-scale datasets that include both WiFi RTT,

Table 3. Comparisons of RTT and RSS properties.

Property	RTT	RSS
Less severely affected by body blockage	**Yes**	No
More robust when interfered	**Yes**	No
Less affected by phone case	**Yes**	No
More sensitive to placements and heading directions of the smartphones	No	No
Has an offset in ranging	**Yes**	No
LoS stability	**Yes**	No
NLoS stability	No	No
More sensitive to interior changes	**Yes**	No



(a) Building floor testbed.

(b) Office testbed.

(c) Apartment testbed.

Figure 16. Layout of the three testbeds. The orange dots show the locations of the RTT-enabled APs. All measurements are taken in the grey areas.

RSS signal measurements, and LoS conditions of each AP for every reference point. For future research purposes, the proposed datasets contain more than 120 scans of WiFi signal measures for every reference point, which would benefit the assessment of the statistical features of WiFi RTT and RSS (see Table 4).

We used three different splits of training and testing sets when assessing the system performance. In addition, the training and testing points did not overlap. 13 RTT-enabled Google APs were set up with respect to real-world placements of the building's APs. The LG G8X ThinQ smartphone, the most reliable device as shown in the previous experiments, was used to collect the WiFi signals. A person held the phone at chest height during the whole recording process.

Table 5 shows a snapshot of the dataset. Measurements recorded in columns AP1 RSS to AP13 RSS are the signal measures received from each

Table 4. The details of the proposed datasets.

Dataset features	Building floor	Office	Apartment
Area	92 × 15 m^2	5.5 × 4.5 m^2	7.7 × 9.4 m^2
Grid size	0.6 × 0.6 m^2	0.455 × 0.455 m^2	0.48 × 0.48 m^2
Reference points	642	37	110
Samples per RP	120	120	120
Data samples	77,040	4,440	13,200
Training samples	57,960	3,240	9,720
Testing samples	19,080	1,200	3,480
Signal measure	WiFi RTT, WiFi RSS	WiFi RTT, WiFi RSS	WiFi RTT, WiFi RSS
Other information	LoS condition of every AP	LoS condition of every AP	LoS condition of every AP
Collection time	3 days	1 day	1 day
Notes	A complex real-world scenario with both LoS and NLoS conditions	A LoS scenario	Contains an AP with NLoS paths for most of the RPs

Table 5. A Snapshot of the proposed WiFi dataset. The value −200 dBm in (a) and 100,000 millimetres (mm) in (b) indicate that the AP is not visible from the current reference point.

(a) WiFi RSS data samples

X	Y	AP1 RSS (dBm)	AP2 RSS (dBm)	...	AP13 RSS (dBm)	LoS APs
1	15	−200	−200	...	−73	12
1	16	−200	−200	...	−70	12
2	0	−200	−200	...	−71	None
2	1	−200	−200	...	−63	12
...	...	...	...	...	...	...
125	15	−74	−47	...	−200	2 3

(**b**) WiFi RTT data samples

X	**Y**	**AP1 RTT (mm)**	**AP2 RTT (mm)**	**...**	**AP13 RTT (mm)**	**LoS APs**
1	15	100,000	100,000	...	5,958	12
1	16	100,000	100,000	...	4,893	12
2	0	100,000	100,000	...	8,716	None
2	1	100,000	100,000	...	10,062	12
...	...	...	...	...	...	...
125	15	10,585	598	...	100,000	2 3

AP. The value −200 dBm indicates that the AP is not visible from the current reference point. Columns X and Y specify the ground truth label of the location, while column LoS APs indicates which APs have a direct LoS to this location. Similarly, an example of the RTT training data is demonstrated in Table 5 (b). The value of 100,000 mm indicates that no RTT signal is received from the AP.

5.2. Empirical results

To evaluate the performance of RTT and RSS fingerprinting-based systems, we adopted nine popular machine learning (ML) and deep learning (DL) algorithms

Table 6. RMSE results of WiFi-based indoor positioning utilising machine learning and deep learning in the building floor dataset. The terms mm and std indicate that the features are pre-processed with standard scaler (std) and min max scaler (mm), respectively.

Method	RTT+RSS	RTT	RSS
KNN	0.781	0.781	1.470
KNN mm	0.971	0.791	1.470
KNN std	0.930	0.791	1.463
K-means	0.786	0.777	1.547
K-means mm	1.028	0.791	1.533
K-means std	0.984	0.785	1.551
LNR	2.999	3.532	3.699
LNR mm	2.995	6.562	8.012
LNR std	3.000	6.646	8.079
RF	**0.688**	0.751	1.382
RF mm	**0.688**	0.752	1.379
RF std	**0.688**	0.751	1.380
GB	0.735	**0.634**	**1.359**
GB mm	0.735	**0.634**	1.360
GB std	0.737	**0.634**	**1.359**
MLP mm	0.738	0.864	1.317
MLP std	0.697	0.692	1.376
DNN mm	0.831	0.748	1.364
DNN std	0.689	0.650	1.460
CNN mm	**0.600**	**0.528**	1.379
CNN std	0.867	1.002	1.391
AE+SVR mm	1.865	1.929	1.338
AE+SVR std	1.089	1.270	**1.244**
Trilateration	N/A	6.776	N/A

to estimate the location, namely K-Means, K-Nearest Neighbours (KNN), Linear Regression (LNR), Random Forest (RF), Gradient Boosting (GB), Multilayer Perceptron (MLP), Deep Neural Network (DNN), Convolutional Neural Network (CNN) and Autoencoder (AE). For AE, a support vector regressor (SVR) was leveraged for positioning estimation. We also used trilateration on RTT data as the baseline accuracy. A desktop with Intel i9-12900K @4.80 GHz CPU, 32GB DDR4 4000 MHz memory, and NVIDIA GeForce 3080Ti GPU was used to perform the positioning algorithms using the Python Scikit-learn and TensorFlow package. Note that, we took into account the offset of the LG smartphone RTT measurement when calculating the trilateration estimations. Root mean squared error (RMSE) is used as an evaluation metric accompanied by the cumulative distribution function (CDF) plot. Furthermore, we applied two scaling methods, standard scaler (std) and min max scaler (mm), on the signal measures. For machine learning or deep learning based indoor positioning, the RMSE results are presented in Tables 6, 7 , and 8, while Figures 17, 18 , and 19 demonstrate the CDF results.

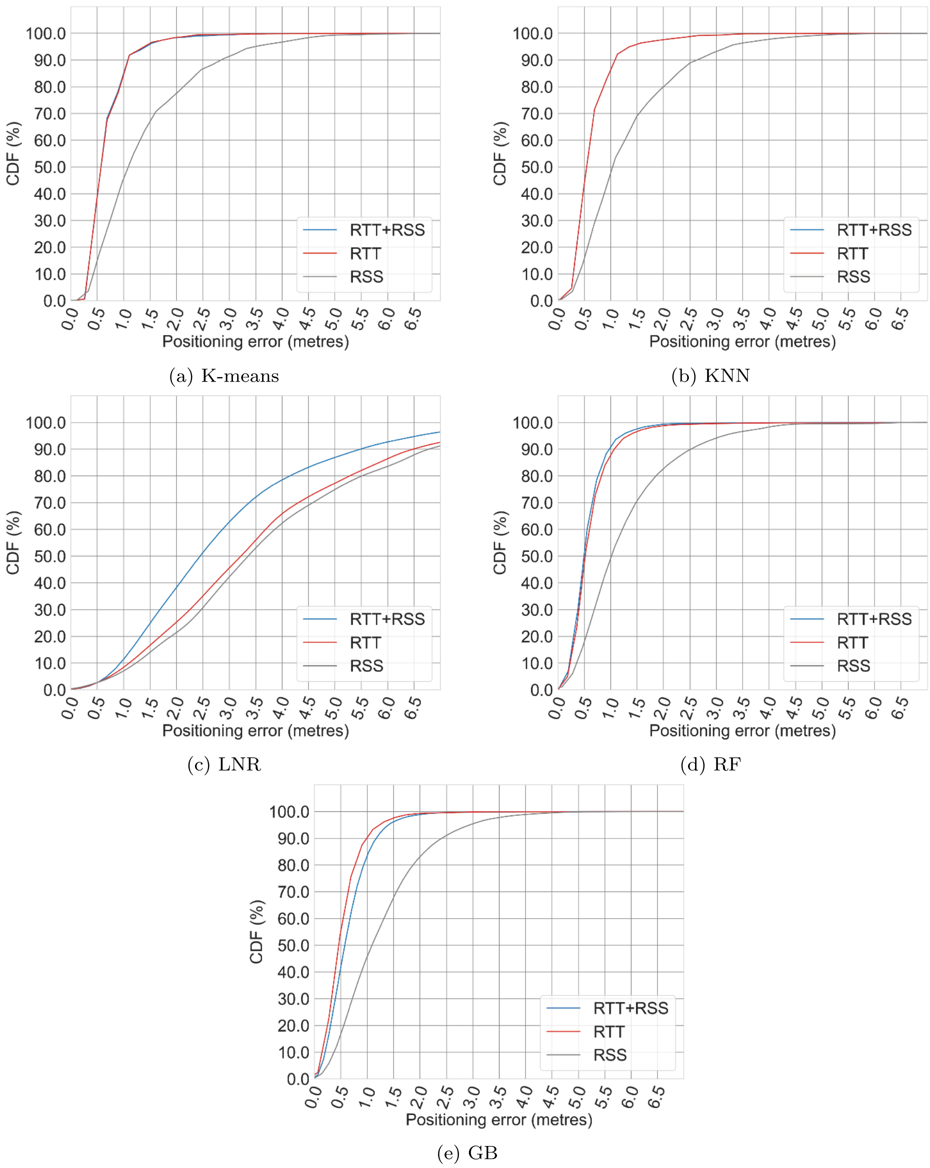
It was observed that WiFi RTT-based fingerprinting utilising ML achieved an accuracy of below 1 metre under all testing conditions, except for LNR-based ones, because LNR is limited to linear relationships. RTT trilateration struggled at about 1.5 metres and over 6 metres accuracy in apartment and

Table 7. RMSE results of WiFi-based indoor positioning utilising machine learning and deep learning for the office room dataset. The terms mm and std indicate that the features are pre-processed with standard scaler (std) and min max scaler (mm), respectively.

Method	RTT+RSS	RTT	RSS
KNN	0.394	0.394	**0.590**
KNN mm	0.593	0.394	0.629
KNN std	0.554	0.399	0.591
K-means	0.406	0.408	0.624
K-means mm	0.631	0.418	0.663
K-means std	0.583	0.418	0.628
LNR	0.860	0.939	0.599
LNR mm	0.619	0.946	0.606
LNR std	0.609	0.944	0.599
RF	0.379	**0.372**	0.607
RF mm	0.381	**0.372**	0.606
RF std	0.380	**0.372**	0.605
GB	**0.356**	0.376	0.650
GB mm	0.357	0.376	0.654
GB std	**0.356**	0.376	0.653
MLP mm	0.406	**0.338**	0.600
MLP std	0.335	0.365	0.709
DNN mm	0.388	0.340	0.658
DNN std	0.367	0.390	0.647
CNN mm	**0.311**	0.366	0.593
CNN std	0.400	0.374	0.627
AE+SVR mm	0.517	0.578	0.597
AE+SVR std	0.435	0.552	**0.573**
Trilateration	N/A	0.723	N/A

Table 8. RMSE results of WiFi-based indoor positioning utilising machine learning and deep learning for the apartment dataset. The terms mm and std indicate that the features are pre-processed with standard scaler (std) and min max scaler (mm), respectively.

Method	RTT+RSS	RTT	RSS
KNN	**0.562**	**0.562**	1.289
KNN mm	0.872	**0.562**	1.289
KNN std	0.860	0.575	1.344
K-means	0.592	0.594	1.465
K-means mm	1.026	0.582	1.445
K-means std	0.963	0.634	1.421
LNR	1.396	1.869	1.389
LNR mm	1.383	1.897	1.389
LNR std	1.365	1.859	1.389
RF	0.609	0.589	**1.279**
RF mm	0.609	0.589	**1.279**
RF std	0.617	0.589	1.280
GB	0.813	0.731	1.333
GB mm	0.813	0.731	1.333
GB std	0.813	0.731	1.333
MLP mm	0.661	0.705	1.237
MLP std	0.634	0.540	1.299
DNN mm	0.622	0.562	1.259
DNN std	0.560	0.540	1.268
CNN mm	**0.508**	**0.458**	1.268
CNN std	0.570	0.504	1.325
AE+SVR mm	1.009	1.255	0.986
AE+SVR std	0.682	0.979	**0.780**
Trilateration	N/A	1.586	N/A



(a) K-means (b) KNN (c) LNR (d) RF (e) GB

Figure 17. CDF of WiFi-based indoor positioning utilising ML with the building floor dataset. Note that in (a) and (b), the RTT+RSS line overlaps with the RTT line.

building floor environments, respectively. The reason fingerprinting was better than trilateration because the signals were heavily attenuated. Such a phenomenon had an impact on RTT measures but benefited the performance of fingerprinting.

We observed that for the apartment testbed that contained an NLoS AP for most reference points, it was difficult for ML-based fingerprinting systems to achieve a better positioning accuracy than the other two scenarios. By analysing the standard deviation of the APs in the apartment dataset, it was observed that

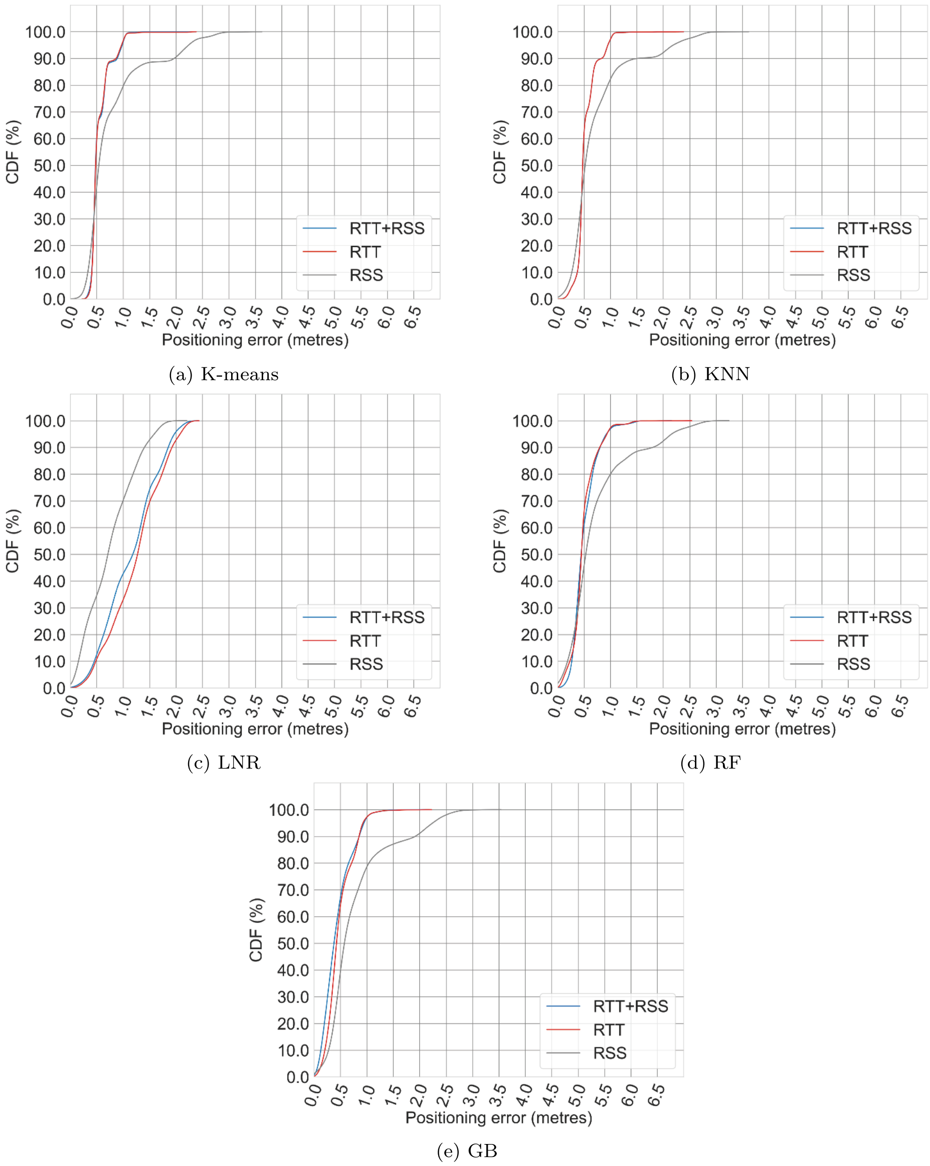
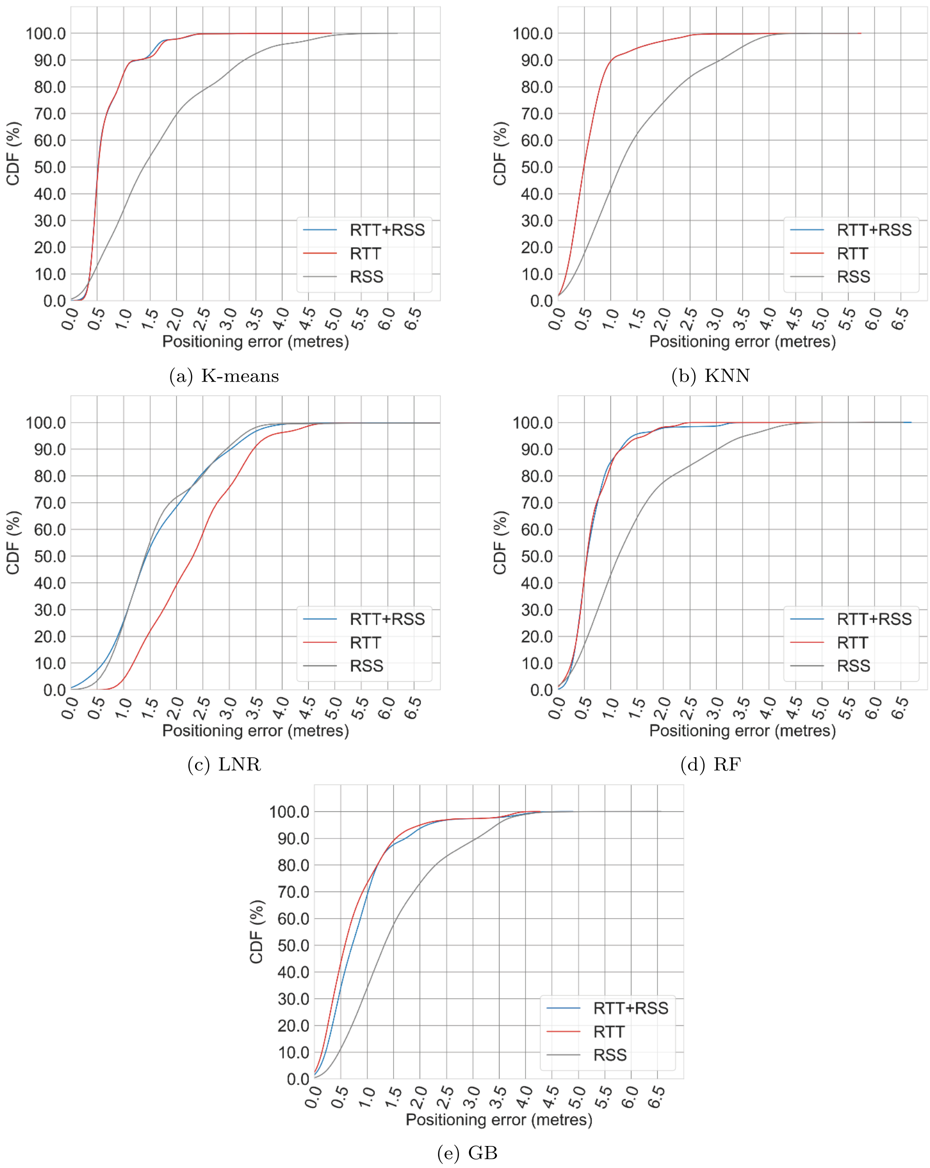


Figure 18. CDF of WiFi-based indoor positioning utilising ML with the office dataset. Note that in (a), (b), and (d), the RTT+RSS line overlaps the RTT line.

the RTT measures only had an average standard deviation below 7,600 mm, compared with the average standard deviation of 39,000 mm and 16,000 mm for the building floor and office LoS datasets, respectively. Furthermore, the standard deviation of the RTT measurements from the NLoS AP was only 4,691 mm, which made the positioning estimations inaccurate based on such similar RTT samples.

Using hybrid RTT-RSS measurements as input features was not as helpful as expected. The RMSE results indicated that introducing RSS features to RTT



(a) K-means (b) KNN (c) LNR (d) RF (e) GB

Figure 19. CDF of WiFi-based indoor positioning for utilising ML with the apartment dataset. Note that in (a), (b) and (d), the RTT+RSS line overlaps the RTT line.

data had only a minor impact on the accuracy most of the time. Also, applying standard scaler and min max scaler on WiFi measurements did not greatly improve the performance of ML algorithms. This was because raw RTT measurements already contained sufficient information for fingerprinting.

From the CDF plots, we observed that RTT-based system could get an accuracy of below 1 metre up to 80% of the time in complex building floor environment, and up to 90% in both building floor and apartment scenarios,

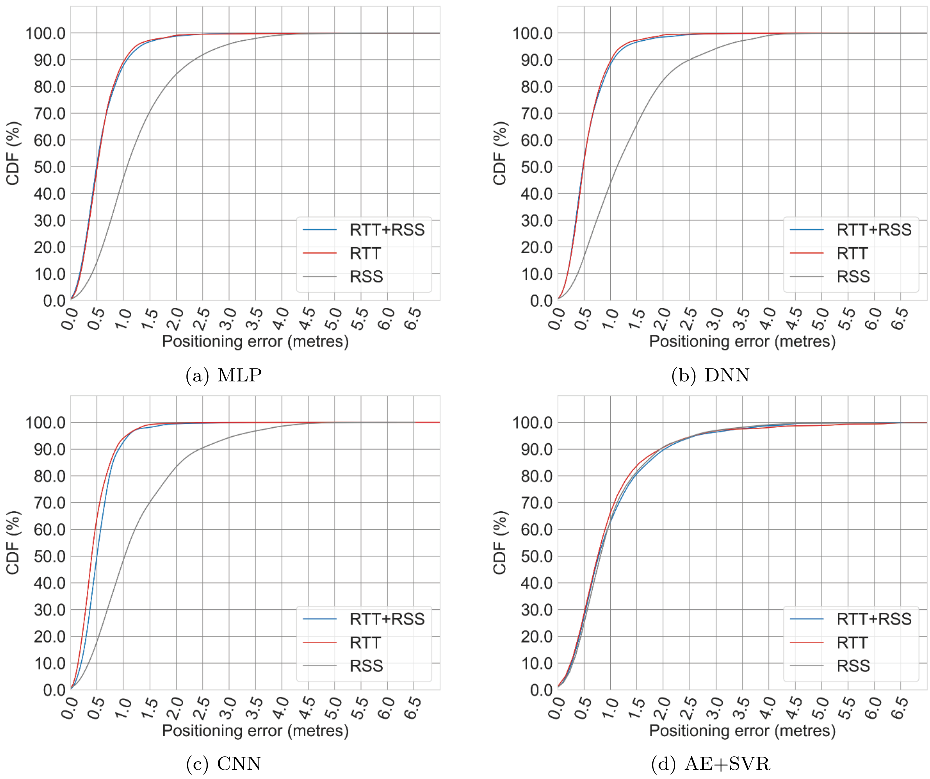


Figure 20. CDF of WiFi-based indoor positioning utilising deep learning with the building floor dataset. Note that in (a) and (b), the RTT+RSS line overlaps with the RTT line. And in (d), all lines overlap with each other.

and even up to 98% in LoS office scenario. The hybrid RTT-RSS-based system had similar results to the RTT-based one by showing its overlapping CDF curves. On the contrary, the RSS-based system got an accuracy of below 1 m less than 60% of the time in the building floor dataset and the apartment dataset, and only 80% in the office room. RSS, due to its less robust nature to the interior changes was producing twice the positioning error, compared to RTT.

For DL-based indoor positioning, the RMSE results are presented in Tables 6, 7 , and 8, while Figures 20, 21 , and 22 demonstrate the CDF results. Note that for AE, an SVR was utilised as a regressor for positioning estimation.

We observed that WiFi RTT-based fingerprinting utilising DL achieved an accuracy of below 1 metre in all testing conditions, except for AE+SVR method. The unsupervised learning process of AE failed to generate sufficient WiFi signal features for robust and reliable indoor positioning. But it was the best DL method for RSS-based fingerprinting among all the tested methods. It was observed that compared to the best ML-based indoor positioning systems, the best DL-based approaches included in this article could have an average improvement of 0.1 metres in positioning accuracy

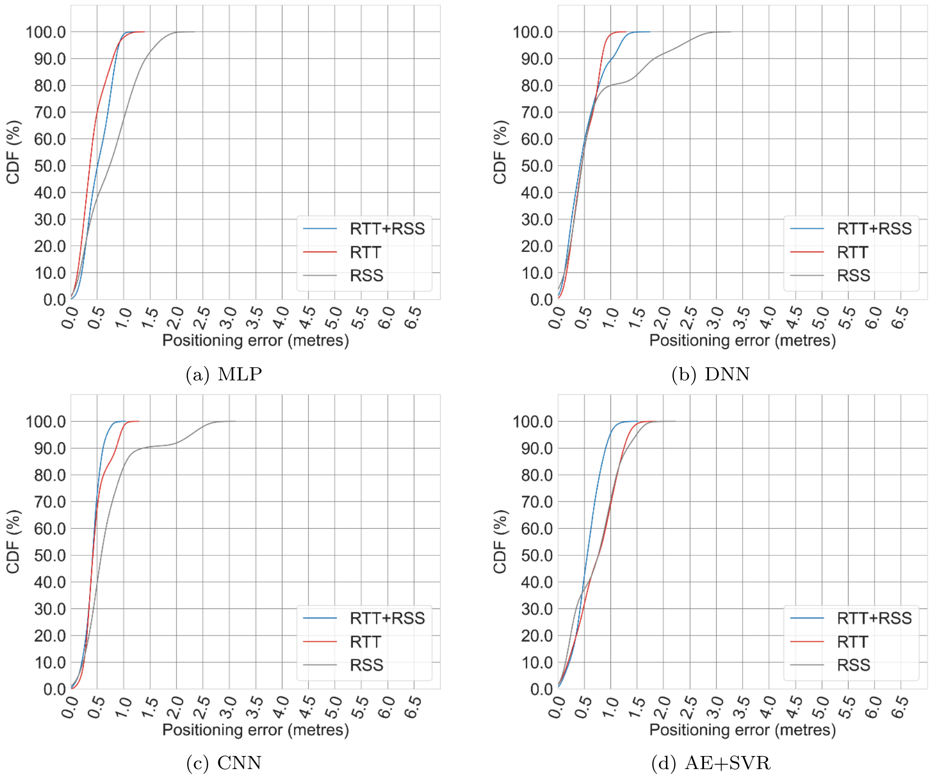
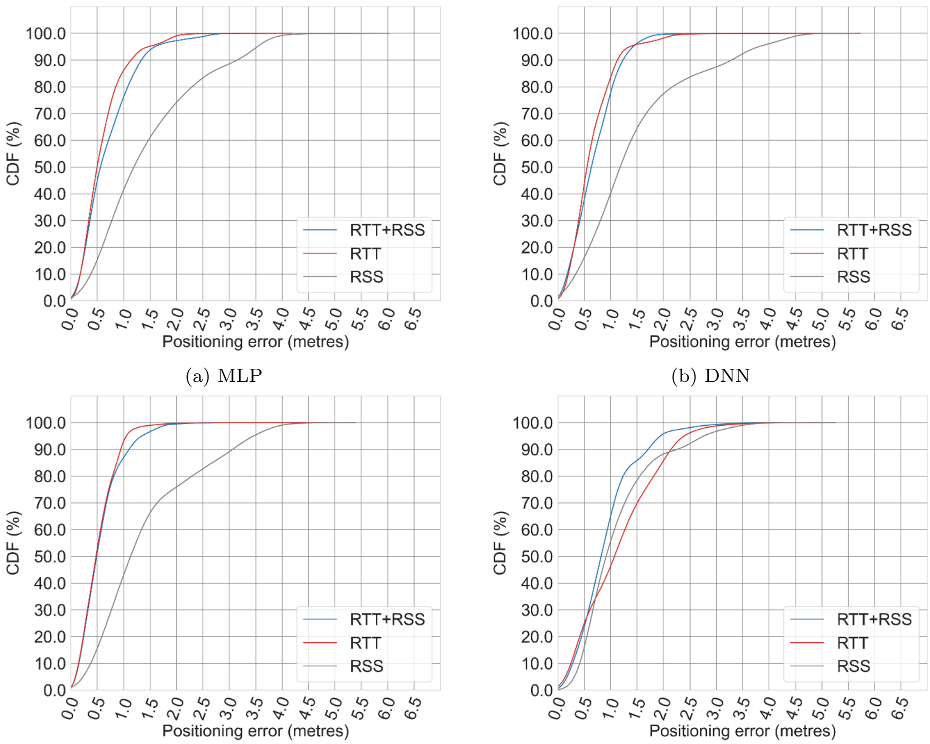


Figure 21. CDF of WiFi-based indoor positioning utilising deep learning for the office room dataset.

for all proposed datasets. Compared to MLP which was the most time-consuming method, CNN had a more efficient performance in positioning estimation. It was illustrated that converting the WiFi signal measures into images and then feeding them to CNN could achieve robust sub-metre level accuracy. Improvement in indoor positioning accuracy was not guaranteed by introducing hybrid RTT-RSS measurements as input features. For CNN with min max scaled data, utilising both RTT and RSS signal measures had an impact on the accuracy for the building floor and the apartment datasets, but that was not always the case for the office room dataset. For AE+SVR method, using hybrid RTT-RSS as input data proved to have the best positioning accuracy.

It was illustrated in the CDF plots that an RTT-based system utilising DL methods could achieve an accuracy of below 1 metre up to 90% of the time in the complex building floor environment, compared with only 80% with ML algorithms. For the office room LoS scenario, DL-based fingerprinting achieved sub-metre level accuracy up to 100% of the time. And for the apartment dataset with a NLoS AP for most reference points, the CNN-based system achieved an accuracy of below 1 metre up to 92% of the time. But for the other three DL



(a) MLP (b) DNN (c) CNN (d) AE+SVR

Figure 22. CDF of WiFi-based indoor positioning for utilising deep learning on the apartment dataset.

methods, only MLP and DNN could achieve an accuracy of below 1 metre 85% of the time. It was observed from these results that NLoS conditions in a small-scale testbed had a huge impact on the positioning accuracy. The hybrid RTT-RSS-based system also had similar performance to the RTT-based one by showing its overlapping CDF curves. In comparison, systems using only RSS signal measures as input data got an accuracy of below 1 metre less than 60% of the time in the building floor dataset and the apartment dataset, and only 85% in the office room.

It was observed in the CDF curves that the DL-based fingerprinting achieved better, more robust, and promising positioning accuracy. Due to its performance of learning unique feature patterns from image-formatted data, CNN proved to be the best positioning algorithm among all methods included in this article. Even in large-scale complex indoor environments, CNN-based indoor positioning systems could get robust sub-metre level accuracy. We also observed that compared to a large-scale complex testbed and a small-scale LoS testbed, it was challenging for fingerprinting methods to achieve better positioning accuracy in the small-scale apartment testbed with an AP that had NLoS path to most reference points. As analysed above, the NLoS AP in a small-scale dataset would generate similar RTT measures most of the time and made it difficult for ML-based fingerprinting. It was observed in the results that NLoS AP had a huge impact on WiFi-based indoor positioning systems.

6. Conclusions

In this article, we performed comprehensive experiments to analyse the properties of WiFi RTT measurement. The experiments were carried out in three complex and realistic indoor environments.

We observed that different smartphones have different robustness in RTT and RSS measures with respect to the AP interference, phone placement, human blockage, heading directions, and NLoS scenario. Among those, human body blockage, the most common issue for real-world indoor positioning, had the greatest impact on the WiFi signal measures. A constant offset was observed in the RTT measurement, which also varied among smartphones and could be unpredictable in the NLoS situation. The building interior had a huge impact on the RTT measurement, making it less stable than RSS. Furthermore, the offset in smartphone RTT measures should be considered carefully for indoor positioning.

To evaluate the baseline performances of machine learning, deep learning-based fingerprinting, and trilateration, three real-world datasets were collected and made publicly available for further research. We demonstrated that RTT-based fingerprinting achieved an accuracy of below 0.7 m with machine learning algorithms and of 0.6 m with deep learning methods, which is 107% better than RSS fingerprinting and 6 m better than RTT trilateration. We concluded that CNN achieved the highest performance in different scenarios among all positioning algorithms investigated in this paper, while AE+SVR was the best method for RSS-based fingerprinting.

For future work, a robust AP LoS condition identification algorithm could greatly improve indoor positioning performance. The system could adopt different weights and positioning algorithms for LoS and NLoS WiFi signal measures. For better positioning accuracy with deep learning algorithms, a more detailed and thorough hyperparameter fine-tuning method would be required.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The three datasets used in this paper are made publicly available here: https://github.com/Fx386483710/WiFi-RTT-RSS-dataset.

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