An Analysis of the Properties and the Performance of WiFi RTT for Indoor Positioning in Non-line-of-sight Environments

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Summary: ***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 environments remains an open research question. To this end, this paper investigates the properties of WiFi RTT in several real-world indoor environments on heterogeneous smartphones. We present a large-scale dataset containing both RTT and received signal strength (RSS) signal measures with correct ground-truth labels for further research. Our results indicated that RTT fingerprinting system delivered an accuracy of below 0.75 m which was 98% better than RSS fingerprinting and 166% better than RTT trilateration, which failed to deliver sub-metre accuracy as claimed.***

Introduction

One of the most popular approaches for indoor positioning is WiFi fingerprinting (Bahl & Padmanabhan, 2000). Such systems used the WiFi received signal strength (RSS) as signal feature, and were known to achieve an accuracy of a few metres on average (Abbas et al., 2019; Xue et al., 2017).

Since the release of the WiFi IEEE 802.11-2016 standard, 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) 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. However, despite its promise in achieving sub-metre positioning accuracy in ideal line-of-sight (LoS) condition, the performance of WiFi RTT in real-world complex, non-line-of-sight (NLoS) indoor environments remained unexplored.

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

The paper's contributions

- *A large-scale real-world WiFi RTT & RSS dataset with correct ground truth labels.* To support the development of future RTT positioning systems, we contribute a dataset containing both WiFi RTT and RSS signal measures on a testbed of more than 92 × 15 m^2 of a campus floor with ground truth labels meticulously marked by post-it notes and manually verified by several human testers. The dataset contains 77,040 location samples from 642 reference points recorded over 3 days and was pre-processed so that the training points and testing points do not overlap.
- *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, etc.
- *Performance ranking of WiFi RTT, RSS, hybrid RTT-RSS fingerprinting and trilateration.* We conducted a comparative analysis on RTT- and RSS-based indoor fingerprinting systems that use different Machine Learning algorithms, and trilateration.

Related work

Systems that leverage WiFi RTT were reported to achieve sub-meter accuracy indoors (Dümbgen et al., 2019; Gentner et al., 2020; Han et al., 2019; Yan et al., 2019). Many have conducted researches to verify the accuracy of the systems based on WiFi RTT with different positioning algorithms, including trilateration (Choi et al., 2020), traditional machine learning (Hashem et al., 2021), and deep learning (Seong et al., 2021). However, the challenges for RTT and RSS in Non-Line-of-Sight (NLoS) environments were also highlighted (Nguyen & Luo, 2015; Nguyen et al., 2021). To make the best of WiFi signals and achieve better positioning accuracy, systems supporting both WiFi RTT and RSS measurements were proposed (Dong et al., 2021; Guo et al., 2019; Hashem et al., 2021). Furthermore, systems were proposed to identify Line-of-sight (LoS) scenarios in which 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 (Guo et al., 2019; Horn, 2020; Gentner et al., 2020; Feng et al., 2022). The biases of such offset in different devices (Choi & Choi, 2020) and in different distances (Sun et al., 2020) were also analysed. Calibration models were leveraged to compensate for such offset: fixed offset (López-Pastor et al., 2021), double exponential (Horn, 2020), linear polynomial, quadratic polynomial (Choi & Choi, 2020). However, to the best of our knowledge, there is still a lack of comprehensive analysis of WiFi RTT measurements in challenging environments.

RTT background

This section overviews the underlying mechanism of WiFi RTT technology.

RTT protocol

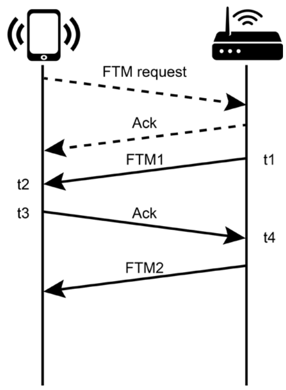


Fig. 1: Overview of FTM protocol. The dash lines show the control messages before the measurement took place.

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 Fig. 1, the 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. Next, the AP will send an FTM message FTM1 to the smartphone and receive back an acknowledgement (Ack). The timestamps (e.g., t1, t4) of the process will be stored and transmitted back to the smartphone through the next FTM2 message.

Therefore, the RTT measurement is defined as:

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

where $(t4 - t1)$ is the time it takes for a single RTT measurement, $(t3 - t2)$ is the time delay inside the smartphone. The distance is then calculated as:

$$Distance = \frac{RTT}{2} \cdot c \qquad (2)$$

where c is the speed of light.

On Android phones, each measuring burst contains 8 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 connection between the AP and the smartphone.

Table 1: The three 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

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, etc.), one of the most common indoor enviroments for WiFi-based indoor positioning. The RTT-enabled smartphones included in this analysis were LG G8X ThinQ (LG), Google Pixel 3 (Pixel) and Nokia 8.5 5G (Nokia) (see Table 1). The Google WiFi router was used as the Access Point for these experiments. We recorded 300 WiFi samples per reference point.

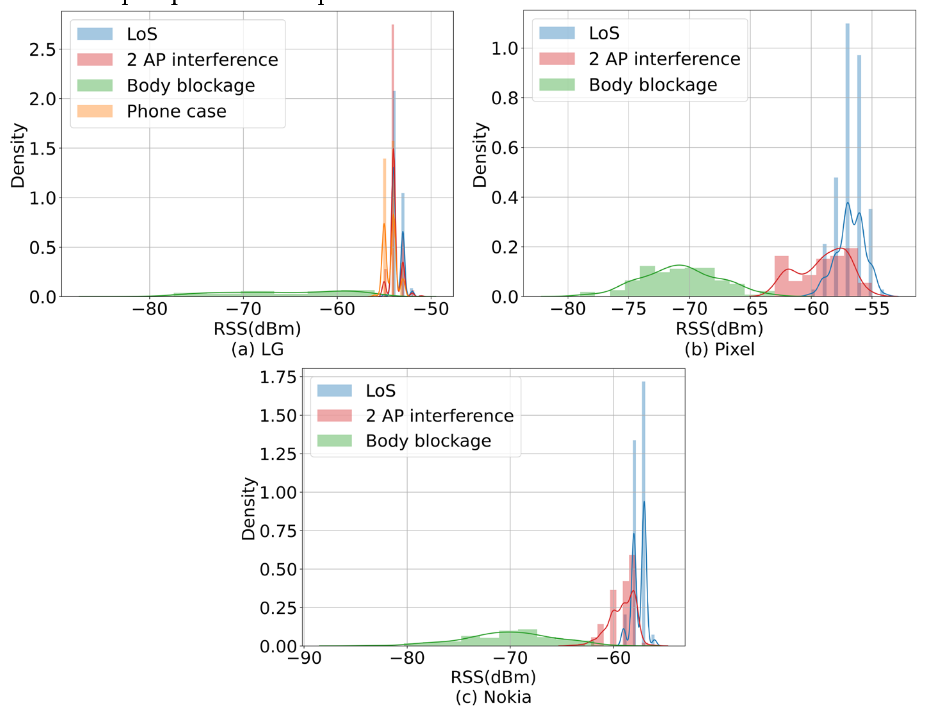


Fig. 2: The WiFi RSS data distribution under LoS, AP interference, and body blockage scenarios. LG G8X ThinQ was further tested with a phone case. The smartphones were set 3 metres away from the Google WiFi AP. Overall, the RSS could be significantly attenuated by the human body.

Body blockage and AP interference

In order to observe the stability of the RTT and RSS signal, we recorded the measures in 3 different situations, including LoS, body blockage and AP interference, as follows.

- To create a LoS, we set the smartphone 3 m away from the AP with no obstacles in-between, while keeping them both at the same height to minimise potential interference.
- To create body blockage, a person stood 20 cm right next to the smartphone. This was to imitate the scenario where the user accidentally blocks the signal transmission.
- To observe the influence of AP interference, we introduced 2 more Google APs in the environment. Furthermore, we put the phone inside a plastic case.

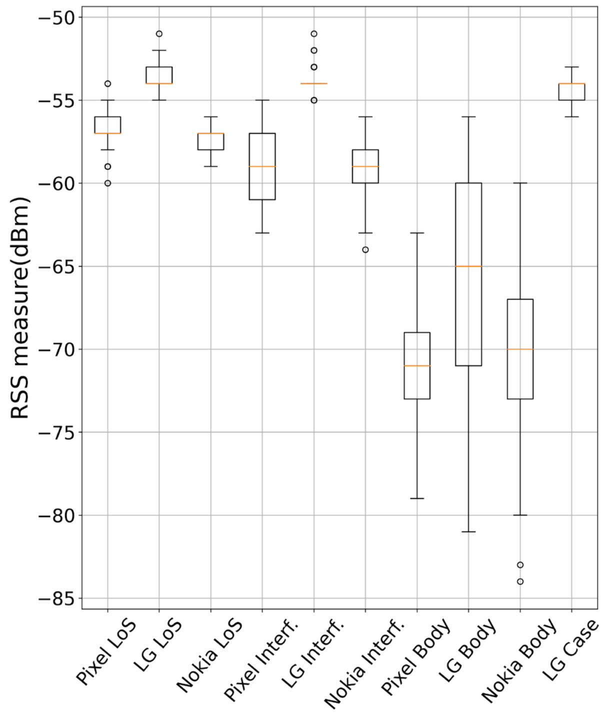
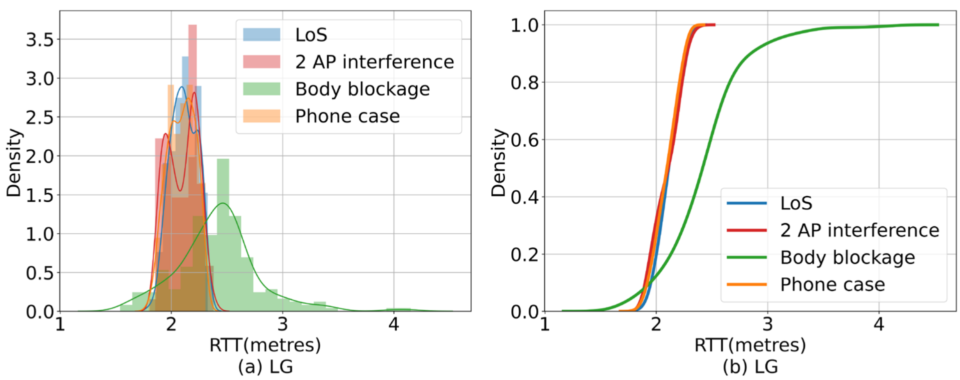


Fig. 3: The comparison of RSS distribution under LoS, AP interference, body blockage and phone case blockage on three smartphones. Longer bar illustrates signal instability. Overall, the RSS could be significantly affected by the human body.

Fig. 2 demonstrates that in the LoS scenario, LG and Nokia had more stable RSS measurements. LG had stronger signals than the other two. We observe that both Pixel and Nokia phones were more vulnerable with AP interference and that they had weaker and less stable RSS. 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 minor impact on the RSS measures (see Fig. 3). Thus, the phone case condition will not be further considered.



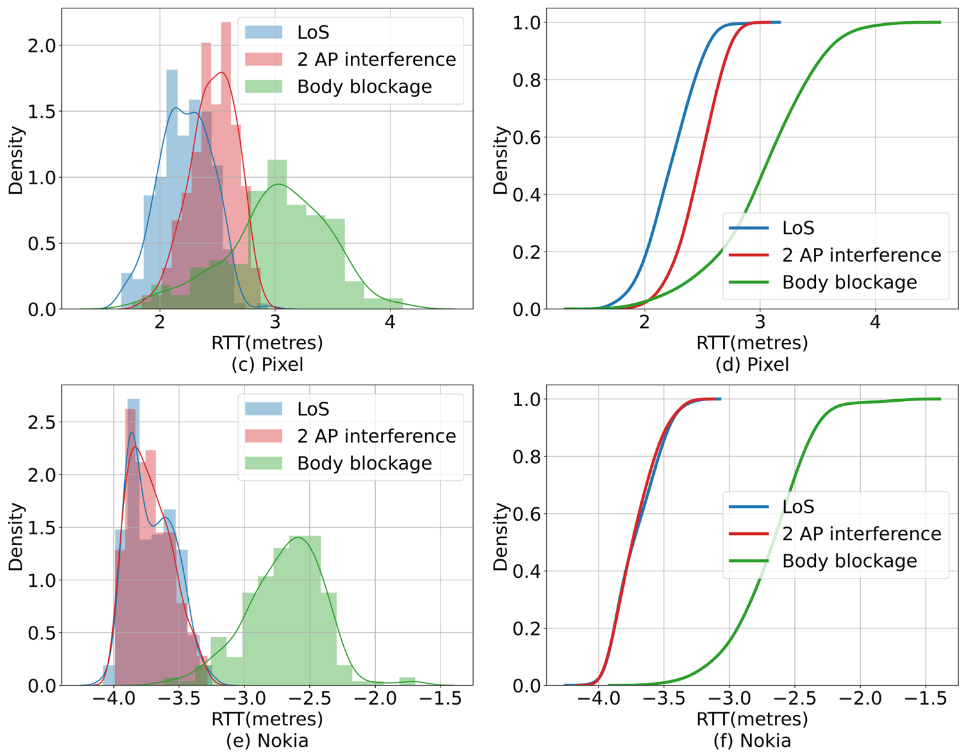


Fig. 4: The raw WiFi RTT data distribution and CDF plot under LoS, AP interference, and body blockage scenarios. LG G8X ThinQ was further tested with phone case blockage. The smartphones were set 3 metres away from the Google WiFi AP. Overall, the RTT could be significantly affected by the human body and the LG phone was more robust to interference.

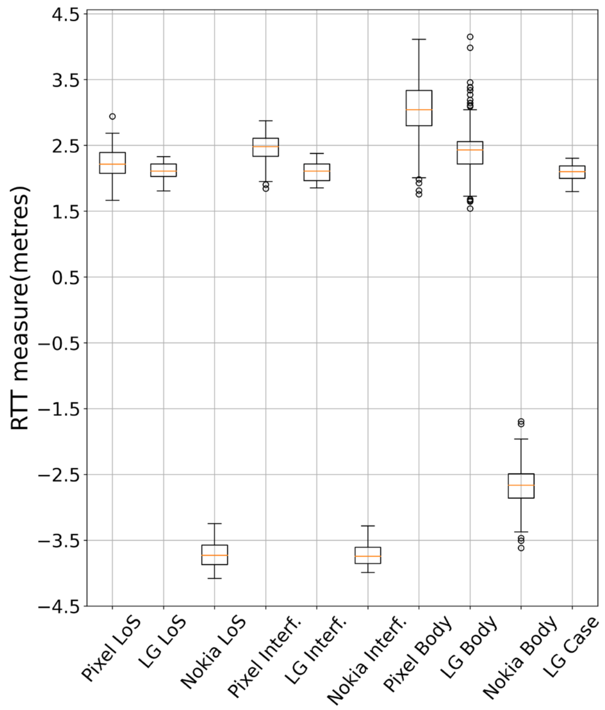


Fig. 5: The comparison of RTT distribution under LoS, AP interference, body blockage and phone case blockage on three smartphones. Longer bar illustrates signal instability. Overall, the RTT measures were much more robust than the RSS counterpart.

The results from the RTT measurement are shown in Fig. 4. We observed that in the LoS scenario, LG had the most stable RTT measure, while Pixel had the worst measures which are 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 is consistent with previously reported research (Guo et al., 2019; Gentner et al., 2020). Nokia had the most surprising offset of more than 6.5 m. Under AP interference, LG and Nokia were more robust than Pixel, and RTT measures were more stable than RSS. When the human body blocked the signals, all three smartphones generated larger RTT measures (see Fig. 5).

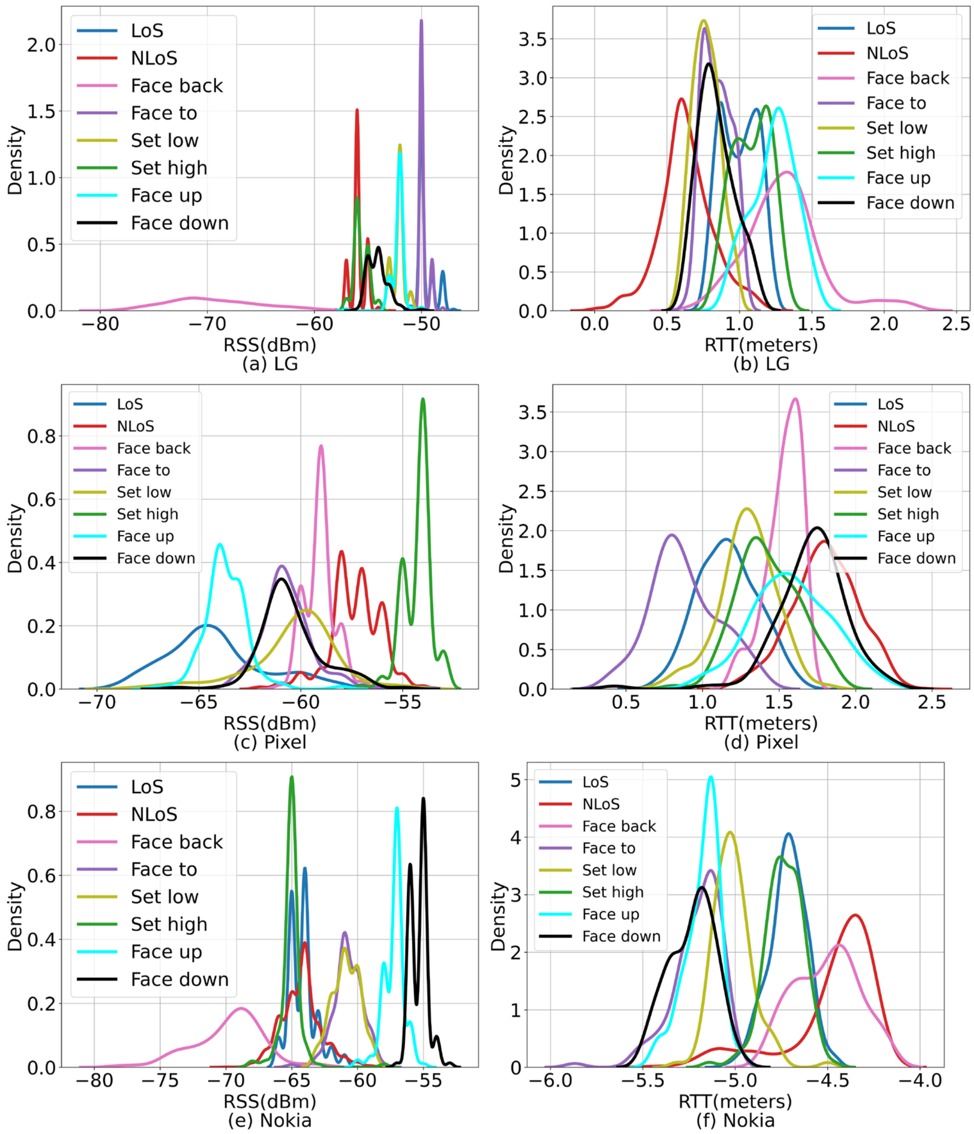


Fig. 6: The WiFi RTT and RSS distributions with different gestures. The smartphones were set 2 metres away from the AP. The scenarios are detailed in **Table 2**. Overall, the RTT and RSS measures could vary significantly depending on the phone's orientation.

Placement and orientation

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

Firstly, we evaluate the RTT and RSS distributions when the smartphone was held in different ways. In this scenario, the smartphone was set 2 metres 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 Fig. 6. 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.

Table 2: The different placements of the smartphone.

Placement	Description
LoS	The back of the phone faces to the AP and is set at the same height as the AP.
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 faces up to the sky
Face down	The screen of the phone faces down to the floor
Set high	The phone is held higher than the AP
Set low	The phone is held lower than the AP

Next, we changed the heading directions of the phone and took the corresponding RTT measures (see Fig. 7). The results demonstrated significant influences on the RTT measure.. with LG and Nokia both produced an offset of up to 0.4 m.

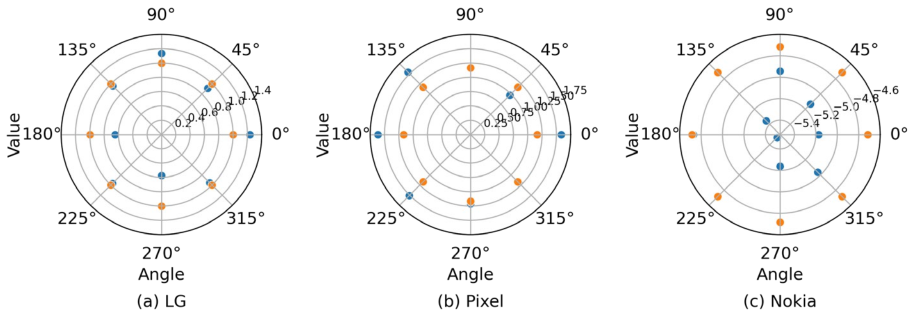


Fig. 7: The WiFi RTT distribution of the smartphone with different heading directions. The smartphone was set 2 metres away and at the same height as the AP with its screen facing up to the ceiling. At angle 0°, the top of the smartphone was aiming right at the AP. The average RTT measures are the blue dots. The orange dots indicate the average LoS RTT measures while the phone is in the LoS scenario. Overall, the RTT measures could vary significantly with different phone's orientations.

Large scale variation

To observe the spatial impact on the signal measurements, we perform ranging experiments under three different environments as shown in Fig. 8. They were office LoS, office NLoS and corridor LoS. The length of the testing area of the three ranging tests was 3 metres, 2 metres and 10 metres, 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 WiFi measurements on the other side. Note that, in all these ranging tests, the smartphone was set at the same height as the AP. We recorded the WiFi signals for 30 seconds per reference point.

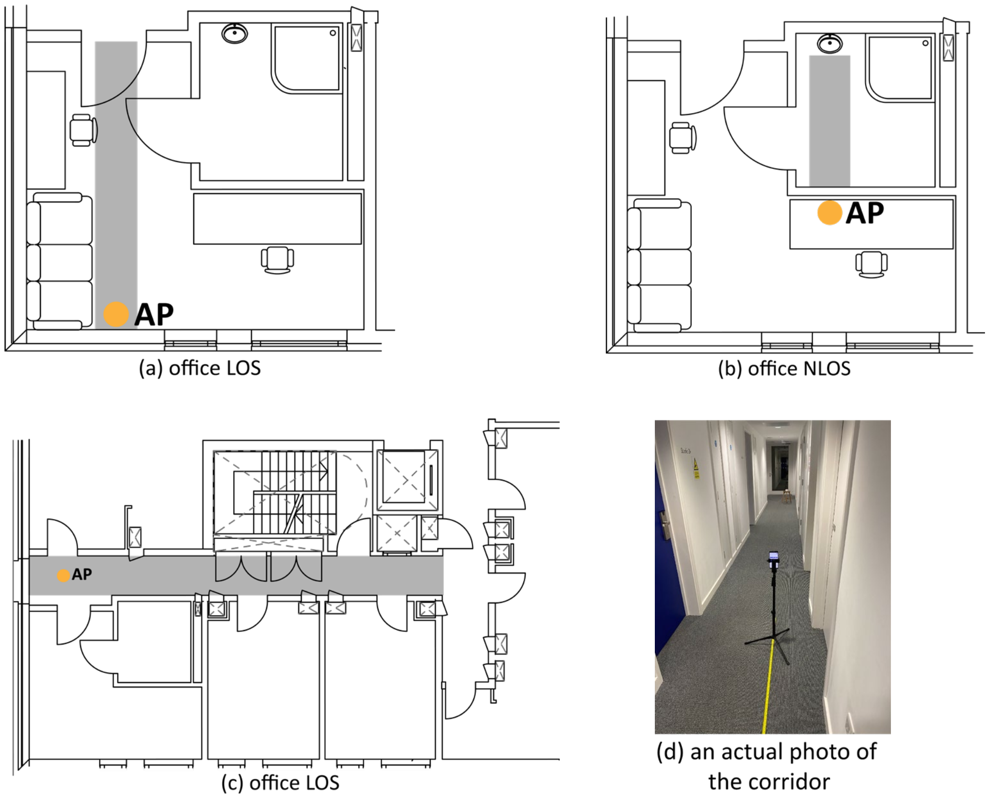
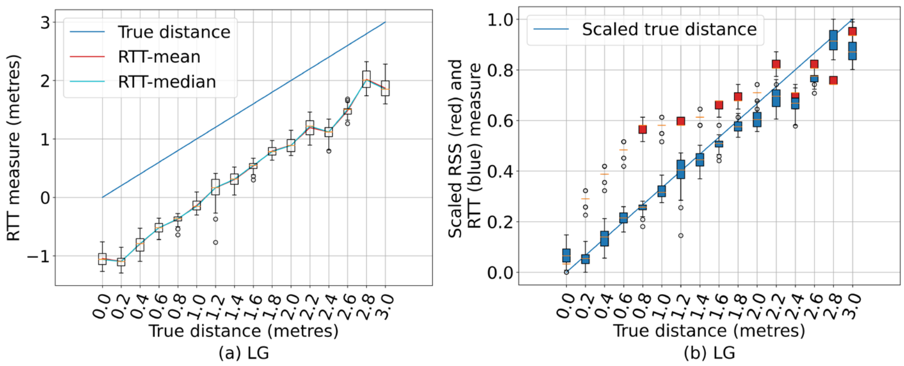


Fig. 8: Overview of the ranging testbeds. The orange dots indicate the location of the AP. The grey area shows the experimental testbed.

The ranging tests' results showed that within 10 metres, the RTT measure will have some constant offset from the true distance, which may be caused by the signal attenuation (see Fig. 9, Fig. 10 and Fig. 11). Such offset varies from one smartphone to another, which is consistent with our findings in previous section *Body blockage and AP Interference.* The NLoS also affects the constant offset pattern of the RTT measure (see Fig. 9 and Fig. 10). In the corridor LoS, where the signals suffered from much more reflections, RSS measure becomes unpredictable as shown in Fig. 11. It was surprising that locations 5 and 8 metres away had the same RSS measure. It could be concluded that the RTT measure was more robust and showed a clear positive correlation to the true distance, compare to RSS measures.



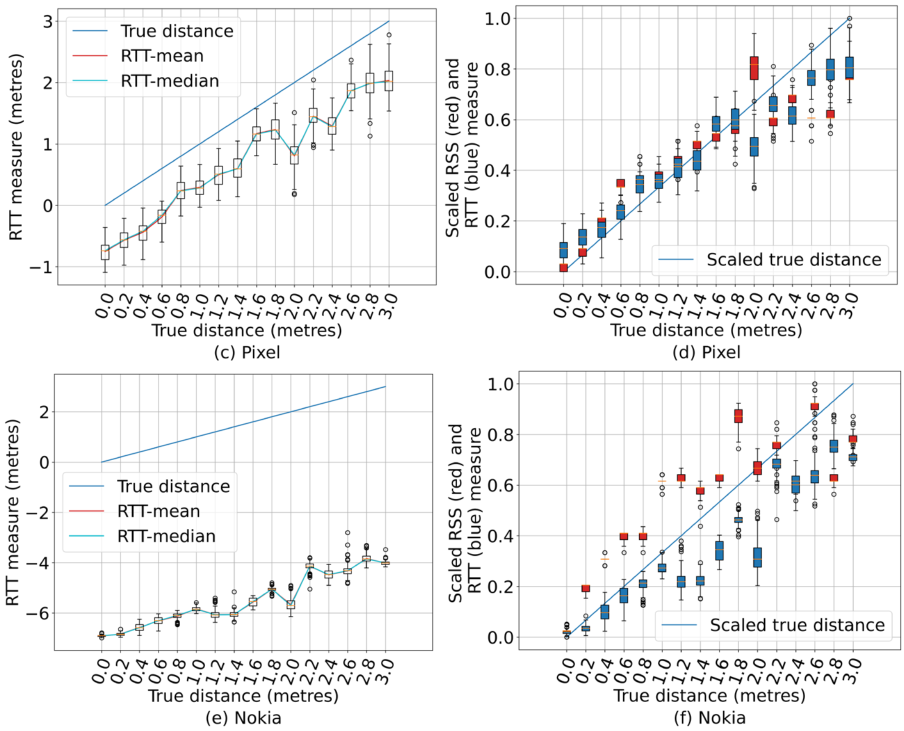
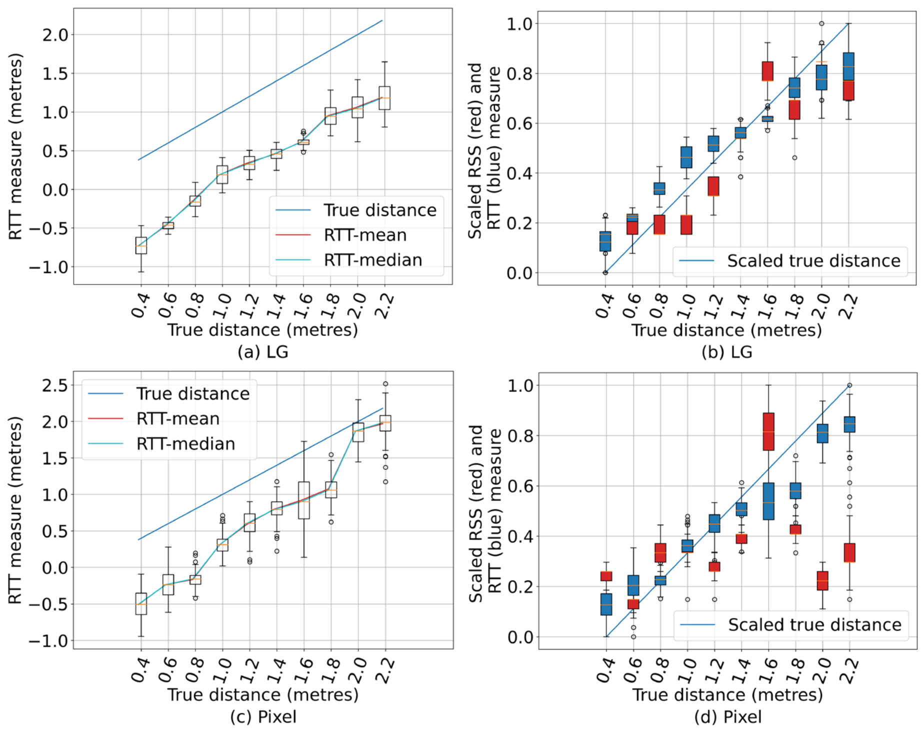


Fig. 9: RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in office LoS scenario. The term scaled means the data was pre-processed, so all of its values are between 0 and 1. Boxplots of RSS measures are in red while those of RTT are in blue. The bigger the scaled RSS is, the weaker the signal is.



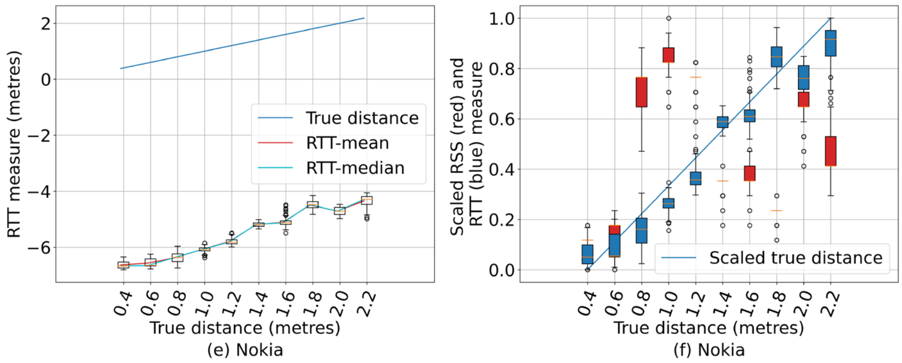


Fig. 10: RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in office NLoS scenario. Boxplots of RSS measures are in red while those of RTT are in blue. The bigger the scaled RSS is, the weaker the signal is.

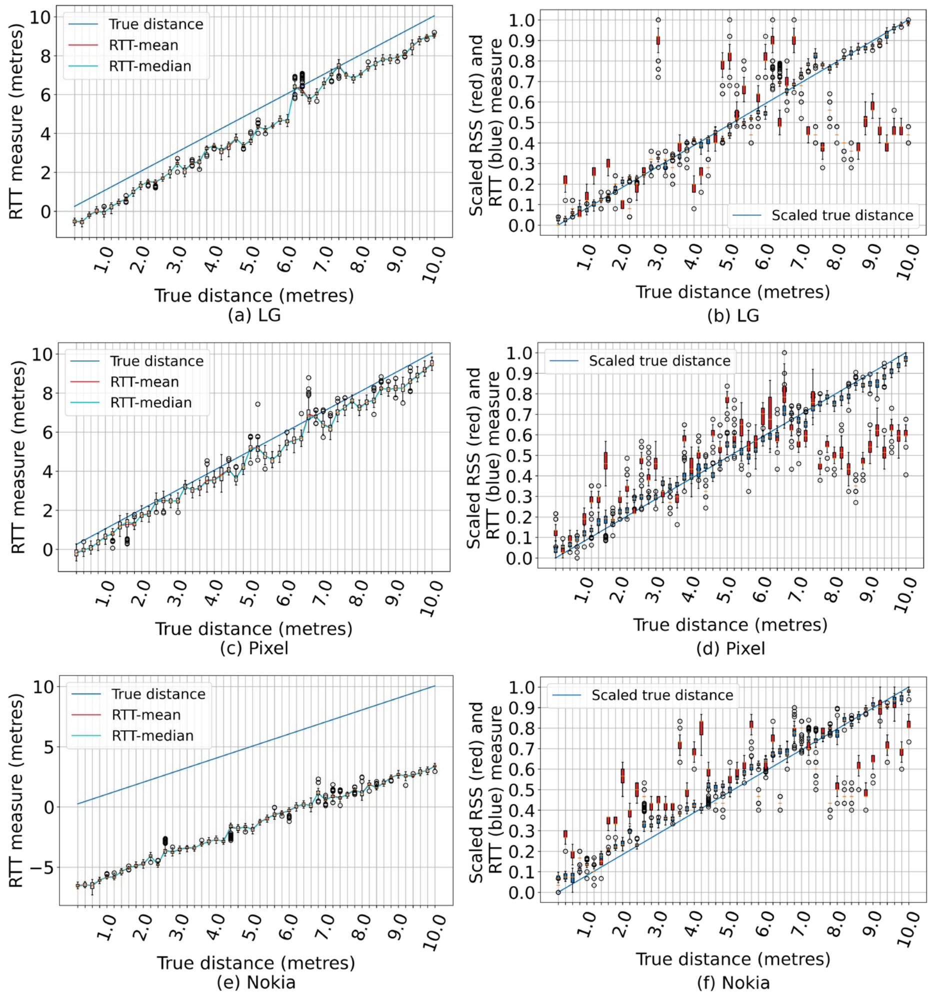


Fig. 11: RTT measures as a function of the true distance and scaled RTT/RSS at different distances from the AP in corridor LoS scenario. Boxplots of RSS measures are in red while those of RTT are in blue. Note that the bigger the scaled RSS is, the weaker the signal is.

Summary of signal properties

Table 3 summaries the properties of RTT and RSS. In short, RTT measures were more stable and more reliable than RSS 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.

Table 3: Comparisons of RTT and RSS properties. The RTT measures were more stable and reliable than RSS in most cases.

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 obvious offset in ranging	Yes	No
Stable in LoS	Yes	No
Stable in NLoS	No	No
More sensitive to interior changes	Yes	No

RTT indoor fingerprinting

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

Fingerprinting

Fingerprinting, one of the most popular techniques in WiFi-based positioning system, consists of an off-line training phase and an on-line positioning phase (Bahl & Padmanabhan, 2000). During the off-line phase, WiFi measurements are collected in an indoor environment into a dataset. In the on-line phase, the positioning estimate of the user will be made based on the matching results of the reported unknown WiFi measurements with those in the dataset.

Experimental setup and data collection

We present a dataset (https://github.com/Fx386483710/WiFi-RTT-RSS-dataset) of the whole fifth floor of the Cockcroft building at the University of Brighton, alongside ground truth coordinates and the LoS APs at each reference point (see Fig. 12). The details of the dataset are shown in Table 4.

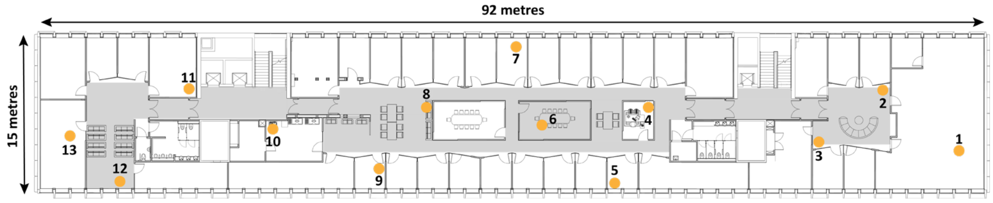


Fig. 12: Layout of the building floor testbed. The orange dots show the locations of RTT-enabled APs. All measurements are taken in the grey area.

Table 4: The details of the proposed dataset.

Dataset features	Details
Area	92×15 m^2
Grid size	0.6×0.6 m^2
Reference points	642
Samples per reference point	120
Data samples	77,040
Training samples	57,960
Testing samples	19,080
Signal measure	WiFi RTT, WiFi RSS
Collection time	3 days

We use three different splits of training and testing sets when assessing the system performance and the training points and testing points do 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 previous experments, was used to collect the WiFi signals. A human holds the phone at chest height during the whole recording process.

Table 5: A Snapshot of the WiFi RSS dataset.

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

Table 6: A Snapshot of the WiFi RTT dataset.

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

Table 7 shows a snapshot of the dataset. Measurements recorded in column AP1 RSS to AP13 RSS are the signal measures received from each AP. The value -200 dBm indicates that the AP is not visible from the current reference point. The columns X and Y specify the ground-truth label of the location, while column LoS APs shows what APs have LoS to this point. Similarly, an example of the RTT training data is demonstrated in Table 8. The value 100,000 millimetres (mm) indicates that no RTT signal is received from the AP.

The same procedure was taken for the second dataset in a 5.46 × 4.45 m^2 office, with a much finer grid size of 0.455 × 0.455 m^2 (see Fig. 13). Three APs were used to cover the whole area.

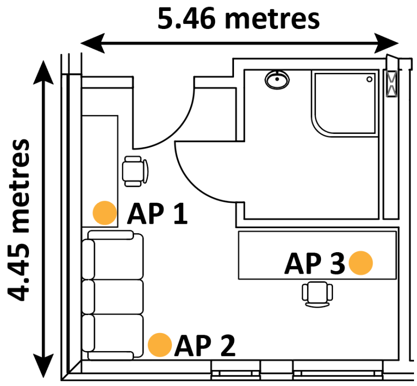


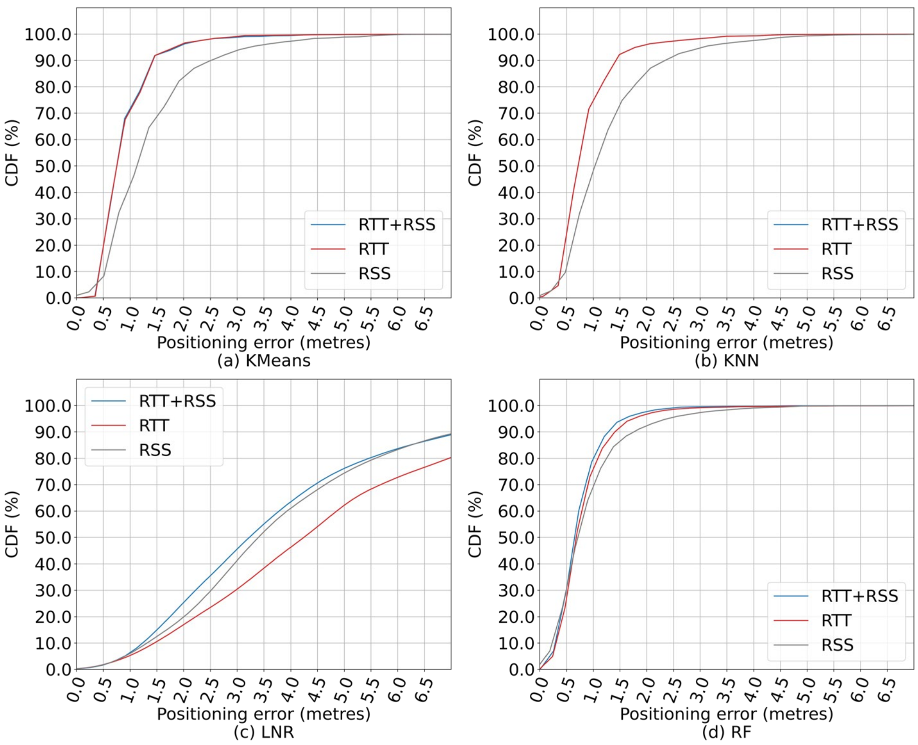
Fig. 13: Layout of the office testbed. The orange dots show the locations of the RTT-enabled APs.

Empirical results

To evaluate the performance of RTT and RSS fingerprinting based systems, we adopt 5 popular Machine Learning algorithms to estimate the location, namely K-Means, K-Nearest Neighbours (KNN), Linear Regression (LNR), Random Forest (RF) and Gradient Boosting (GB). We also used trilateration on RTT data as the baseline accuracy. An MSI GP66 laptop with Intel i7-10870H @ 2.20GHz CPU and 24GB DDR4 3200MHz memory was used to perform the positioning algorithms using the Python Scikit-learn package. Note that, we took into account the offset of the LG smartphone RTT measurement when calculating trilateration estimations. Root Mean Squared Error (RMSE) is used as an evaluation metric accompanied by the Cumulative Distribution Function (CDF) plot. Furthermore, we applied scaling methods, Standard Scaler (std) and Min Max Scaler (mm), on the signal measures. The RMSE results are presented in Tables 7 and 8, while Fig. 14 and Fig. 15 demonstrate the CDF results.

Table 9: RMSE results of WiFi-based indoor positioning in the building floor dataset. The term mm and std indicate that the features are pre-processed with Standard Scaler (std) and Min Max Scaler (mm), respectively. RTT-based fingerprinting could achieve an accuracy of below 1 metre.

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**
Trilateration	N/A	1.971	N/A



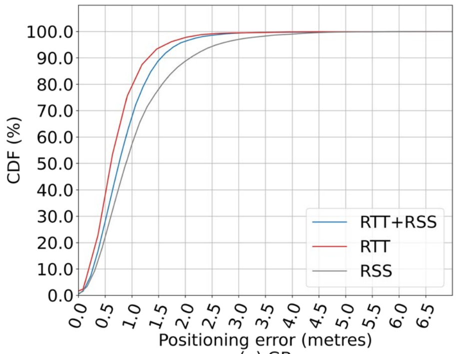


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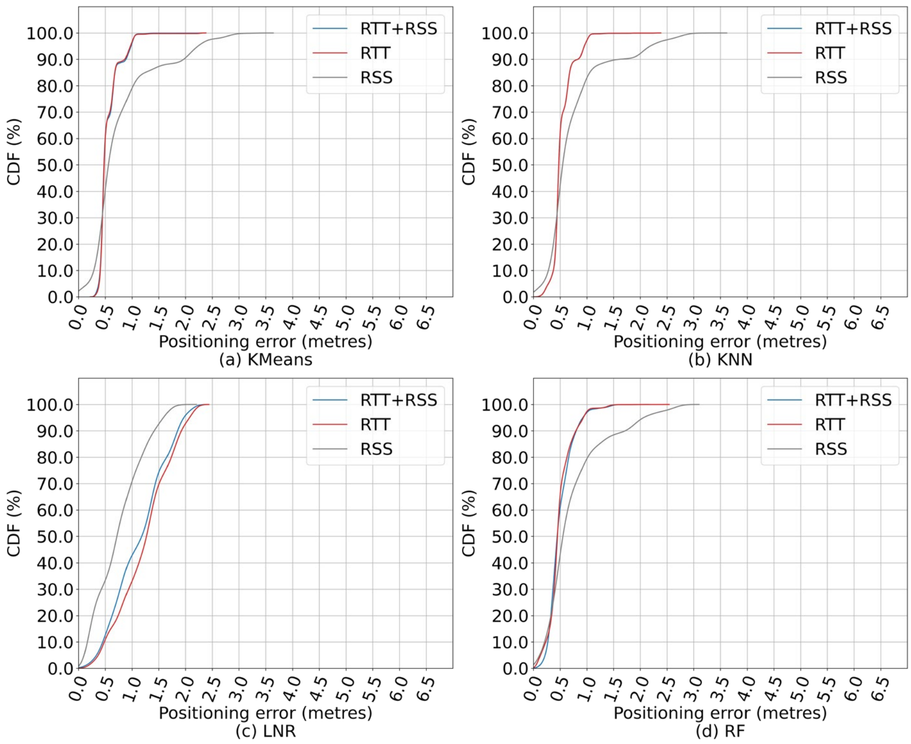
Fig. 14: CDF of WiFi-based indoor positioning with the building floor dataset. Note that in (a) and (b), the RTT+RSS line overlaps with the RTT line. RTT-based system could achieve an accuracy of below 1 metre, 80% of the time.

It was observed that WiFi RTT-based fingerprinting 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 2-metre accuracy in our indoor environments. The reason fingerprinting was better than trilateration was that the signals were heavily attenuated. Such phenomenon had an impact on RTT measures but benefits the performance of fingerprinting. Using hybrid RTT-RSS measurements as input features was not as helpful as expected. The RMSE results indicated that introducing RSS features to RTT data had a minor impact on the accuracy most of the time. Also, applying Standard Scaler and Min Max Scaler on WiFi measurements did not improve the preformance. This was because raw RTT measurements already contained sufficient information for fingerprinting.

Table 10: RMSE results of WiFi-based indoor positioning for the office room dataset. The term mm and std indicate that the features are pre-processed with Standard Scaler (std) and Min Max Scaler (mm), respectively. RTT-based fingerprinting could achieve an accuracy of below 1 metre in LoS office scenario.

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
Trilateration	N/A	1.040	N/A



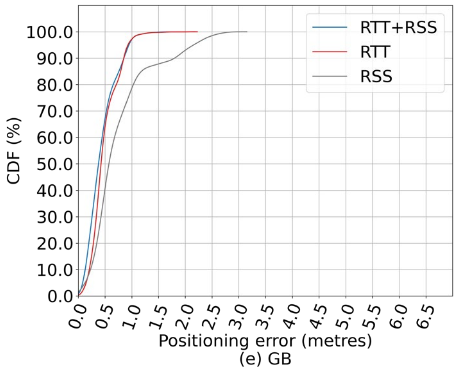


Fig. 15: CDF of WiFi-based indoor positioning for the office room dataset. Note that in (a) and (b), the RTT+RSS line overlaps the RTT line. The RTT-based system could achieve an accuracy up to 1 m, 98% of the time.

From the CDF plots, we observe 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 98% in LoS office scenario. The hybrid RTT-RSS-based system has similar results to the RTT-based one by showing its overlapping CDF curve. On the contrary, the RSS-based system gets an accuracy of below 1 m less than 60% of the time in the building floor dataset, and only 80% in the office room. RSS, due to its less robust nature to the interior changes was giving twice the positioning error, compared to RTT.

Conclusions

In this paper, we performed comprehensive experiments to analyse the properties of WiFi RTT measurement. The experiments were carried out in multiple complex but everyday indoor environments.

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

To evaluate the positioning accuracy of WiFi RTT-based system, we collected two real-world datasets with manually verified ground truth labels. We demonstrated that RTT-based fingerprinting achieved an accuracy of below 0.75 m, which is 98% better than RSS fingerprinting and 166% better than RTT trilateration.

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