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Effect of Body-Environment Interaction on WiFi Fingerprinting

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LIST of ABBREVIATIONS

LBS = Location Based Service

GPS = Global Positioning System

AP = Access Point

RSS = Received Signal Strength

IPS = Indoor Positioning System

ToA = Time of Arrival

TDoA = Time Difference of Arrival

RP = Reference Point

kNN = k Nearest Neighbor

WkNN = Weighted k Nearest Neighbor

CDF = Cumulative Distribution Function

LOS = Line of Sight

NLOS = No Line of Sight

TP = Test Point

WLAN = Wireless Local Area Network

CHAPTER 1
INTRODUCTION

In recent years, LBSs have become very popular with the development of modern communication technologies. In particular, the increased variety of commercial applications has established the demand for indoor LBSs. However, due to the complexity of the indoor environment, it is usually difficult to provide a satisfactory level of accuracy in most applications. For outdoor environments, the well-known GPS is used to locate the position of the target device, but in order to ensure reasonable accuracy, it requires a LOS between the components of the GPS infrastructure and the target device. This is the main reason why the GPS system is not suitable for indoor positioning. The increased deployment and the widespread popularity of WLAN have opened a new opportunity for indoor localization. Therefore, WiFi-based positioning systems are a possible solution for the indoor positioning challenge, given that they are suitable in terms of both cost and accessibility. Among different positioning techniques, the fingerprinting one is a promising solution for indoor positioning, because it also allows the reuse of the existing WiFi infrastructure, without any additional hardware. Fingerprinting operates in two phases: offline and online. During the offline phase, the RSS values (fingerprints) are collected at previously-selected positions, referred to as RPs. During the online phase, the location of the user is determined by comparing the online RSS readings with the offline observations. Among different comparison and estimation algorithms, the kNN and WkNN are possible approaches.
It is important to clarify that several factors affect the achievable accuracy of fingerprinting-based system. In particular, the most important ones are related to the significant variability of the WiFi signal indoor propagation. Among the others, one possible factor, already analyzed in previous works, is the user/device orientation during the fingerprinting phases.

The present work focuses on the experimental analysis of the impact of user/device orientation on the achievable accuracy of a WiFi fingerprinting IPS. In particular, the work is organized as follows: Section 2 reports the main results obtained in previous work regarding the analysis of the effect of user's presence and device orientation on the RSS values. A brief introduction to previous experimental results obtained at the Department of Information Engineering, Electronics and Telecommunications (DIET) of Sapienza University of Rome are also presented. Section 3 introduces a general model for a WiFi fingerprinting IPS in which a kNN/WkNN algorithm is exploited for the estimation phase. Experimental results of previous works showing the impact of the device orientation on the achievable positioning accuracy are also reported.

Section 4 reports the results of the experiments performed at DIET Department regarding the impact of orientation on the WiFi signal propagation and on the positioning accuracy, respectively. Finally, Section 5 summarizes the results and suggests guidelines for future work.

CHAPTER 2
RELATED WORK

In recent years the analysis of positioning techniques and systems of wireless devices have aroused considerable interest within the research community, because of the increasing users' request for so-called LBSs.

The most important positioning system for LBSs is the well-known GPS; however, GPS is tailored for providing position information in outdoor environments and it cannot be used in indoor environments, because of GPS signals cannot penetrate buildings.

This is the main reason why the implementation of accurate and real-time indoor positioning solutions is under study exploiting different technologies. Moreover, it is clear that indoor LBSs require higher positioning accuracy than outdoor ones. However, nowadays, it is still difficult to find a good trade-off between the level of accuracy and the complexity for this kind of system.

Different wireless technologies have been studied for the implementation of indoor positioning systems; however, in light of reusing pre-existent indoor communication infrastructures, a widely adopted choice is the use of Wifi APs already deployed in the area.

In particular, by exploiting the inverse proportionality between the AP-Device distance and the RSS, it is possible to approximately locate the device with cost-effective solutions, given the possibility to easily obtain the RSS values without any additional hardware.

The major challenge for accurate RSS based positioning comes from the high variability of RSS values given the dynamic and unpredictable nature of radio channel, due to several aspects such as shadowing, fading, multipath phenomena, device orientation, human being presence, etc.

In particular, the effects of user's presence and device orientation on the WiFi signal propagation have been widely investigated and main results from previous works are briefly reported in Sections 2.1, 2.2 and 2.3, respectively.

2.1 Effect of user's presence on RSS

In [1] it was experimentally proved that the user's presence close to the receiver device antenna plays a significant role in both experienced RSS mean value and variance, as clearly reported in Figure 2.1.

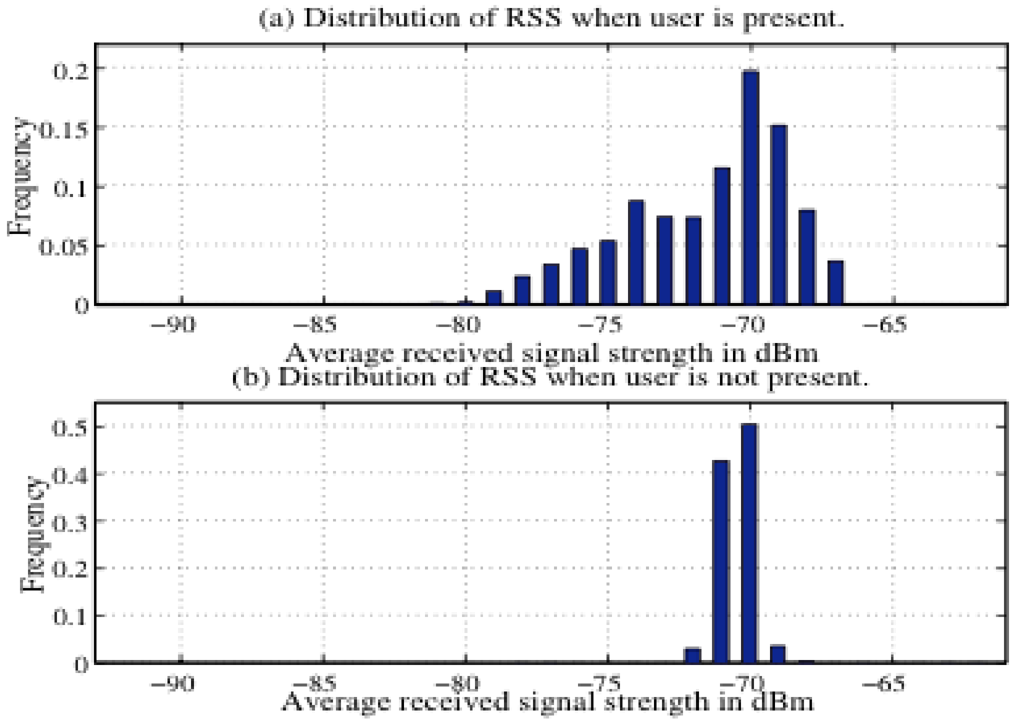

Figure 2.1 Comparison of histograms of RSS [1]

In this experiment, the distance between the WiFi APs and the device was about 7 meters and RSS values were recorded during two hours.

In Figure 2.1(a) the data were recorded when the user was present (during the first hour), while in Figure 2.1(b) RSS were recorded when the user was absent (during the second one). Results in particular show that the user's body influences the RSS distribution by spreading the range of RSS values by a significant amount.

2.2 Effect of user's orientation on RSS

Another important factor is the user's orientation; because the body of the user can attenuate the RSS in a specific orientation but not in the other.

Table 2.1   RSS [dBm] from AP1. [1]

Statistics	North	West	South*	East
Sample Mean	-51.42	-49.73	-59.05	-53.18
Standard Deviation	4.89	4.98	3.69	3.93

Table 2.2   RSS [dBm] from AP2. [1]

Statistics	North	West*	South	East
Sample Mean	-79.95	-83.63	-77.82	-79.24
Standard Deviation	1.79	2.20	1.60	1.50

Tables 2.1 and 2.2 summarize the experimental results obtained in [1] when RSSs from two different APs were collected in a same reference location, by varying the user orientation every 15 minutes.

No obstructing objects were present between the first AP and the receiver, while they were present for the second AP. In the first case the distance was about 6 meters while in the second case it was about 7 meters. Moreover, Tables 2.1 and 2.2 report in both cases the particular device orientation leading to the presence of the user's body between the AP and the device (South for the first AP and West for the second AP, respectively).

Results suggest that while evaluating the orientation effect in a single location, this affects the signal propagation leading to slightly different RSS values for each orientation, and the lowest RSS values when the user obstructed the transmission direct path.

2.3 Experimental analysis at DIET

Similar experimental analysis was also carried out at the 2nd floor of the DIET Department, that is also the area of interest of the present work, and main results are reported in Figures 2.2 and 2.3 [ref_Carla].

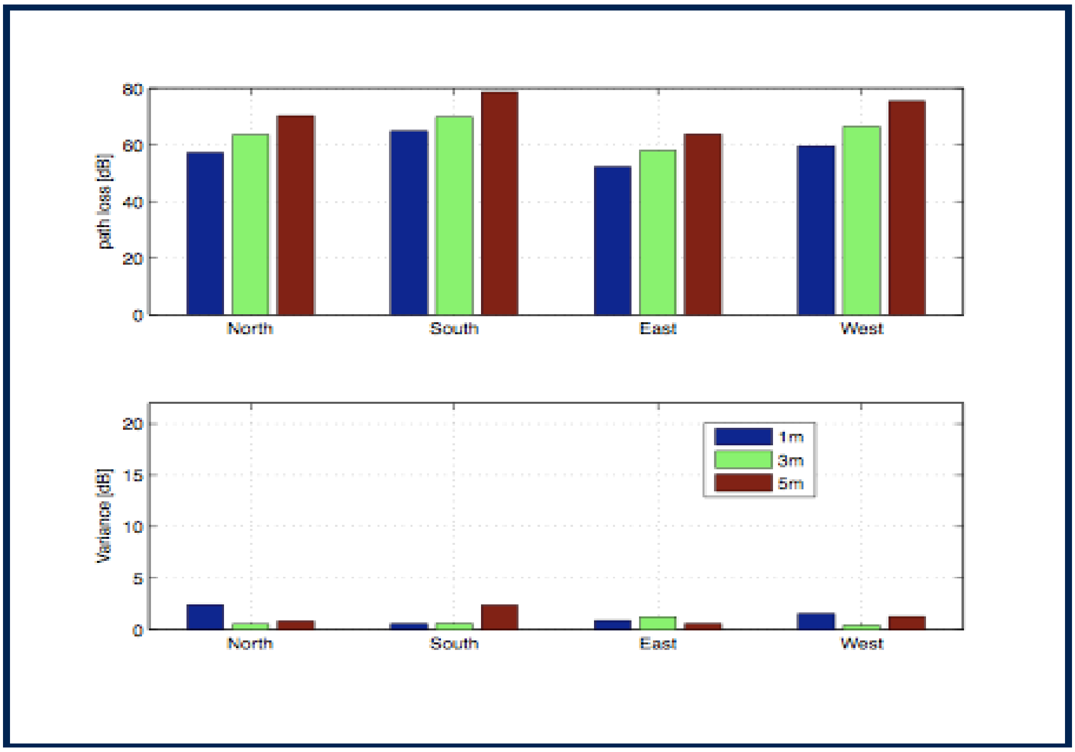

Figure 2.2   Histograms of average path loss and variance (Without user; 1m, 3m, 5m distance from the AP) [ref_Carla]

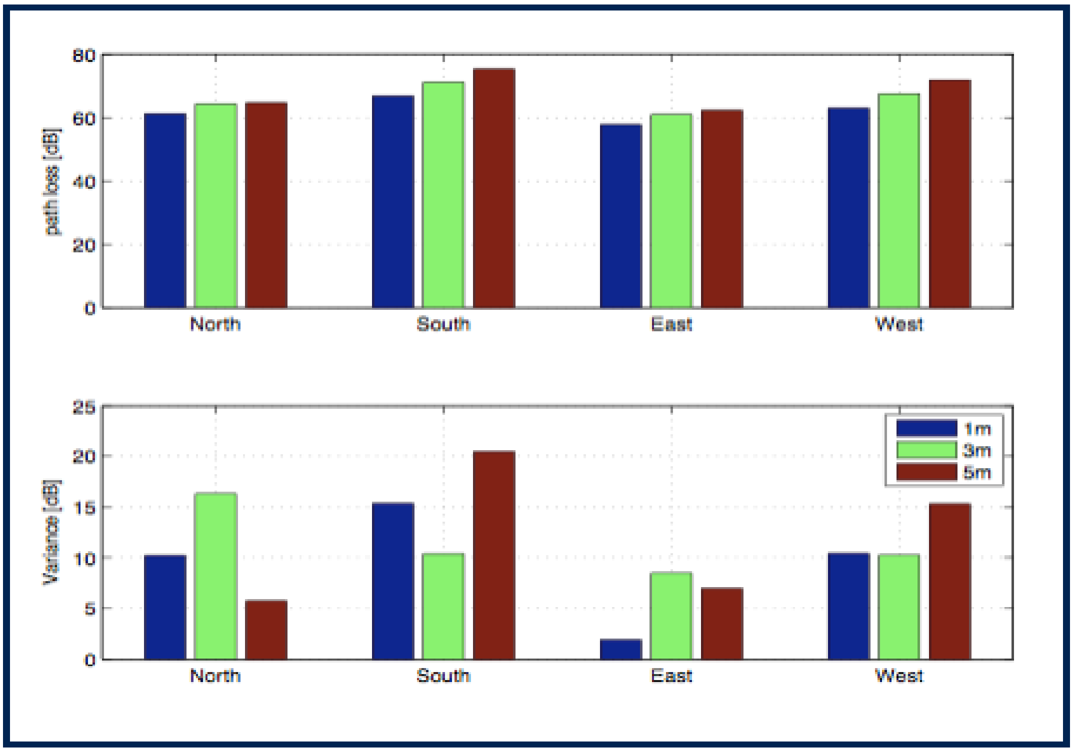

Figure 2.3   Histograms of average path loss and variance (With user; 1m, 3m, 5m, distance from the AP) [ref_Carla]

Considering that the aim of this work was the detailed study of the impact on the orientation of the WiFi signal propagation, the measures were taken in a controlled environment consisting of an empty room and the presence/absence of the user handling the device, in order to minimize the impact of other variability factors. Considered a growing distance AP-Device of about 1, 3 and 5 meters, a maximum number of 110 RSS samples were recorded, for each orientation and both user presence/absence cases.

In Figures 2.2 and 2.3 we can see that, as expected, by increasing the AP-Device distance the experienced path loss increases.

Furthermore, by comparing the results obtained for user presence/absence cases, we can observe that in the first case the range of measured values is more spread, leading to a higher values of the variance.

In light of the previous results, the purpose of this thesis is twofold and can be summarized as follows:

1) Extend the analysis of the orientation impact to multiple reference locations, taken at various distances from several APs placed at DIET. This leads to leave the controlled environment hypothesis (in which the previous tests were carried out) in favor of a more realistic scenario where the orientation impact is not isolated.
2) Study the possibility of using the results obtained in 1) in the implementation of a WiFi fingerprinting-based positioning system at DIET.

For these reasons, the measurements campaign is changed and details of it are reported in Section 4; instead general guidelines on the positioning system are reported in (Section 3.1) together with a brief review on related work (Section 3.3).

CHAPTER 3
EXPLANATION OF THE INDOOR LOCATION METHOD BASED ON FINGERPRINTS

3.1 Introduction to WiFi fingerprinting IPS

Studies on indoor WiFi signal propagation, briefly reported in Section 2, are particularly relevant for the design and implementation of WiFi-based IPSs as will be detailed in Section 4.

In general, several wireless communication technologies can be used for indoor localization purposes and two main implementation approaches are proposed: the first one consists of using a dedicated wireless infrastructure, while the second one consists of using an existing wireless infrastructure.

By focusing on the second approach, that is more cost-effective than the first one, and considering the widespread dissemination of WiFi, many WiFi-based IPSs have been proposed in recent years.

Traditional localization methods are based on two consecutive localization steps:

1) Ranging: estimation of distances between the user device and the APs through the evaluation of signal propagation features such as, for example, RSS, ToA, TDoA;
2) Triangulation: estimation of user's location by exploiting the results obtained in the ranging phase.

By noting that the ranging phase described above assumes the knowledge of the exact positions of the APs, another approach, widely known as fingerprinting, and not requiring this information, is proposed in the context of WiFi-based IPSs.

The fingerprinting approach can be divided in two phases: the offline and the online phase. During the first one (also known as "calibration phase") a radio map of the indoor area is created, containing the RSS values (fingerprints) measured at selected locations, referred to as RPs, from the WiFi APs perceived in the area. This radio map is loaded and stored in a database. Note that in order to counteract the propagation variability, several measurements (*samples* or *scans*) are taken in each RP and then averaged, in particular when a deterministic algorithm is used during the estimation phase. Once the database is created, during the online phase, the position of the user device is estimated by comparing the RSS fingerprint of the user device with the RPs ones. Details on a possible estimation algorithm used in the online phase will be given in Section 3.2.

It is worth nothing that the offline phase could be time expensive because in general it requires the RPs placement and several measurement campaigns. Moreover, it is clear that a trade-off exists between the measurement effort of the offline phase and the achievable positioning accuracy of the online phase.

As already introduced at the end of Section 2 the main goal of this work is the study and the experimental analysis of a WiFi-based fingerprinting IPS at DIET, that takes into account the possible impact of device orientation on the signal propagation. To do so, more details on the estimation algorithm used are provided in Section 3.2; a brief review on previous works studying the impact of orientation on IPSs is then provided in Section 3.3. Finally, Section 4 reports the implementation choices at DIET.

3.2 Estimation algorithms: kNN and WkNN

In general, there are several algorithms that can be used to calculate the user's position during the fingerprinting online phase. One of them is the kNN [7].

The kNN algorithm estimates the user device position by computing the centroid of the k RPs having the *most similar* RSS fingerprints with respect to the online RSS reading, as expressed in Equation (1):

$$\hat{p} = \frac{\sum_{n=1}^{k} p_n}{k} \qquad (1)$$

where:

$p_n = (x_n, y_n)$ is the position of the n-th RP;

$\hat{p} = (\hat{x}, \hat{y})$ is the estimate of the unknown device position in the 2D coordinates system defined for the area of interest;

The concept of similarity introduced above implies the evaluation of a properly-defined similarity metric sim_n between each n-th RP fingerprint and the online RSS reading.

By nothing that, in the context of kNN, sim_n is only used for selecting the k most similar RPs, another algorithm can be introduced and indicated as WkNN [4] [6] [7].

In this case the values of sim_n are also used as weighting coefficient in the evaluation of the centroid, as indicated in Equation (2):

$$\hat{p} = \frac{\sum_{n=1}^{k}(sim_n)\, p_n}{\sum_{n=1}^{k} sim_n} \qquad (2)$$

Both kNN and WkNN algorithms are quite easy to implement but the estimation accuracy is highly dependent on different factors. For example, an important factor is the choice of the value of k to be taken into account in the centroid evaluation. Moreover, another important factor is the choice of the similarity metric to be computed.

Regarding the selection of the value of k, a very popular solution is to choice a fixed number independently from the position to be estimated. It is clear that this is a sub-optimal solution in some cases: for example, it could happen sometimes that if k is not changed during the positioning process, neighbors far from the mobile station might be included in the k nearest neighbors. In this case including the far RPs in the positioning algorithm could decrease the accuracy. Therefore, eliminating some neighbors far from the mobile station is necessary.

Regarding the choice of similarity metric, a very popular choice is the use of the inverse Minkowski distance, evaluated as follows:

$$D = \left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{\frac{1}{p}} \qquad (3)$$

Where p indicates the distance order, X = $(x_1, x_2, \dots, x_n)$ and Y = $(y_1, y_2, \dots, y_n)$ are the online RSS reading and a generic RP fingerprint, respectively. Moreover n indicates the fingerprints length, that is the number of perceived APs in the area of interest. Finally note that when p = 2 the generic Minkowski distance turns into the widely popular Euclidean distance. Equation (4) shows the WkNN estimation formula when a Minkowski distance is used as a similarity metric:

$$\hat{p} = \frac{\sum_{n=1}^{k}(D^{-1})\, p_n}{\sum_{n=1}^{k}(D^{-1})} \qquad (4)$$

3.3 Analysis of user's orientation: impact on positioning accuracy

In this Section related work addressing the impact of user/device orientation on positioning accuracy are briefly reported, together with several proposed solutions. In [3] the SMARTPOS system is introduced; it is an IPS based on deterministic WiFi fingerprinting, enhanced with the use of a digital compass.

Experimental results in [3] show that SMARTPOS can reach a satisfactory positioning accuracy making use of the user's orientation. In particular, during the offline stage, four fingerprints were created for each RP, one for each cardinal direction of the building, by averaging five scans for each direction. During the online stage the user's orientation was firstly estimated by using the digital compass; then, one out of four databases (the one having the nearest orientation with respect to the user one) was selected and the RPs within it were used for estimating the position in a WkNN approach. Results show an improvement of about 40 cm on the mean positioning error if the orientation information is used as described above, in particular for a W3NN algorithm.

Another important experiment regarding the impact of user's orientation on positioning performance is reported in [8]. Two different environments were considered: an office and a gym. For both environments the offline phase was carried out by varying two opposite orientations. Moreover, two more measurement campaigns were carried out in the same orientation and used for testing the system performance. Figures 3.2 and 3.3 show the CDF of the localization error when different combinations of offline/online measurements are used. Results point out that by choosing the same orientation for both phases the system accuracy slightly increases, respect to the case of having different orientation for the two phases. This is true even changing the number of considered APs.

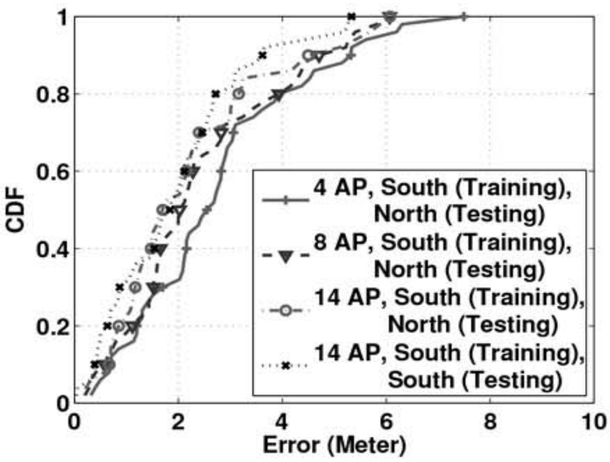

Figure 3.1 CDF curve in office environment [ref_8]

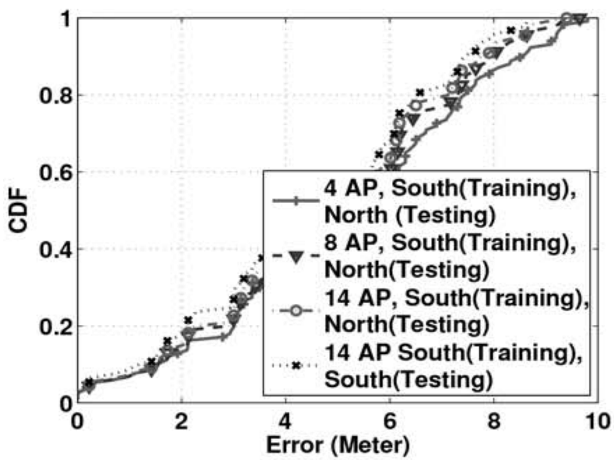

Figure 3.2 CDF curve in gym environment [ref_8]

An exhaustive experimental analysis on WiFi fingerprinting is reported in [2]. Even in this case the impact of user's orientation was analyzed. Two radio maps were created: the first one considered four orientations for each RP and used the average RSS value as a fingerprint, meanwhile in the second one for each RP the average RSS value was obtained by only using one orientation. Experimental results show that the first radio map leads to an improved positioning accuracy.

In [9] the RADAR system is presented. Even in this case four different orientation were considered for each RP. However, in this case, only the fingerprints having the maximum RSS values were selected for the estimation phase. Results show that the above selection improves the accuracy of location estimation. Moreover, similarly to [8], positioning error evaluation was done by considering opposite orientations between offline and online phase, and results show a fairly significant degradation in the accuracy of location estimation.

CHAPTER 4

DESIGN OF A WIFI-BASED FINGERPRINTING IPS AT DIET

Given that the goal of this work is the analysis of an IPS that may exploit the orientation effect, measurements are taken in a scenario more realistic with respect to the one in [ref_Carla]. Experimental analysis in [ref_Carla] were carried out in a fixed location for a single LOS AP, by considering multiple large sets of measurements, one for each selected orientation.

On the contrary, in the present work a real fingerprinting-based system has been created and analyzed: $N_{RP} = 34$ RPs have been measured in the area of interest, that is half of the DIET 2nd floor (approximately 21×12 m^2). For each RP, $O = 4$ orientations have been considered (referred to as North, South, East and West) and $q_{RP} = 20$ samples have been measured for each orientation. This led to the definition of 4 RSS fingerprints for each RP, obtained by averaging the set of samples. Figure 4.1 summarizes the measurement campaign by highlighting the RPs positions and the chosen orientations. Note that, for each RP, the LOS/NLOS condition also depends on both the position of the generic AP in the area and the particular orientation in the RP. Note also that the reference systems for the environment and the device jointly move during the measurement campaign and that the device antenna is located in the upper left side.

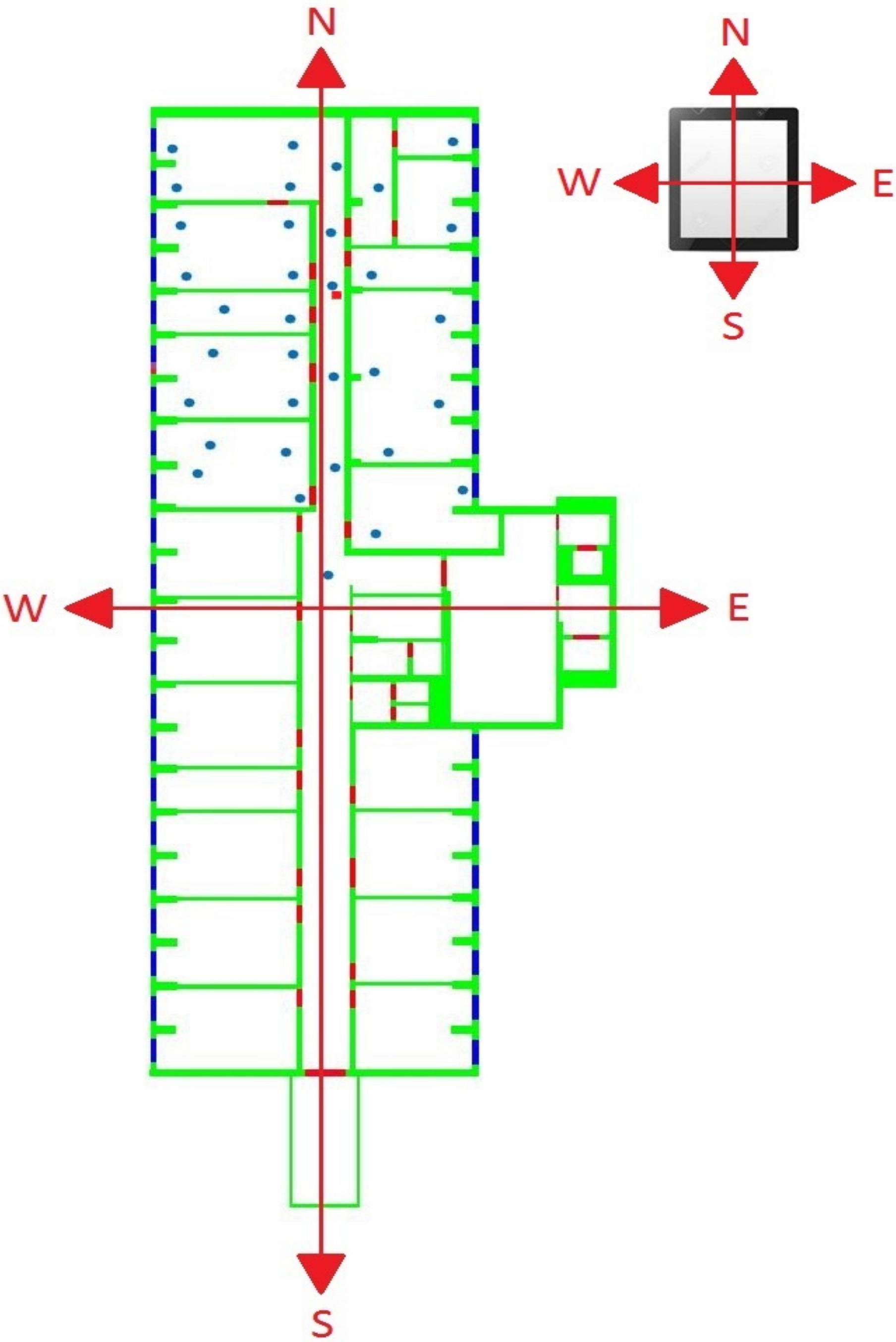

Figure 4.1 RPs measurement campaign at DIET 2nd floor: schematic of cardinal directions (orientations) for 1) the environment and 2) the device, 3) RPs set (blue dots) and 4) a fixed AP (red square)

A second set of measurements, acting as TPs, has been taken at $N_{TP} = 19$ randomly distributed positions, and subsequently used in order to evaluate the positioning system accuracy. $q_{TP} = 10$ samples have been taken for each TP and each orientation. This led to the definition of 4 online RSS readings for each TP.

Both RPs and TPs measurement campaigns have been taken with a Samsung Galaxy Note 10.1 by using android-based application WiFi Compass; as reported in Figure 4.1 the application has been used to create a radio map of the environment by storing for each RP the list of RSS values from all nearby APs.

Figure 4.2 Screenshot of WiFi Compass

4.1 Impact of orientation on the WiFi signal propagation

In this section we present the experimental analysis on the impact of orientation on the WiFi signal propagation.

Once the four oriented RP databases have been created and the total set of APs detected in the area discovered, the first experiment has been focused on analyzing the possible impact of orientation from an environmental point of view. Two different approaches have been carried out:

1. Approach I: for each AP and orientation, the RSS values have been averaged on the total set of RPs (TPs), in order to understand if the APs are perceived at different RSS levels, dependently on the orientation;

2. Approach II: for each RP (TP) and orientation, the RSS values have been averaged on the total set of APs, in order to understand if the averaged RSS perceived within each RP (TP) is changing dependently on the orientation;

Figures 4.3 and 4.5 show the results obtained for Approach I, while Figures 4.4 and 4.6 show the results obtained for Approach II, for the RP set and the TP set, respectively.

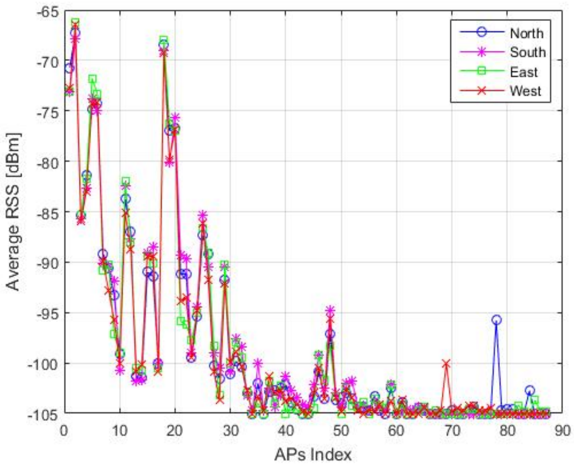

Figure 4.3 Approach I (RP set)

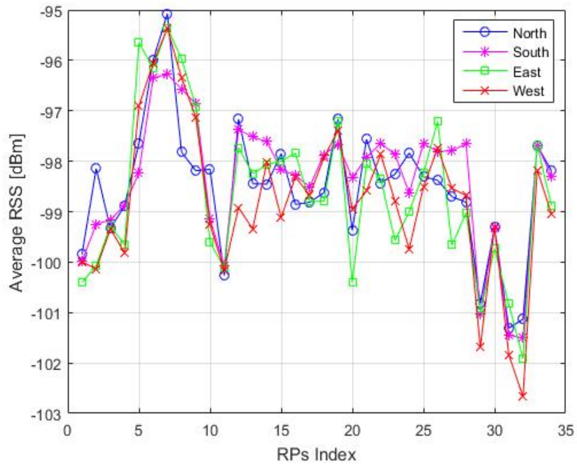

Figure 4.4 Approach II (RP set)

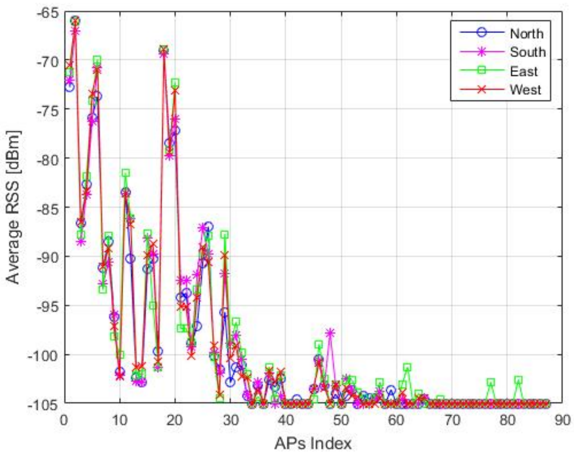

Figure 4.5 Approach I (TP set)

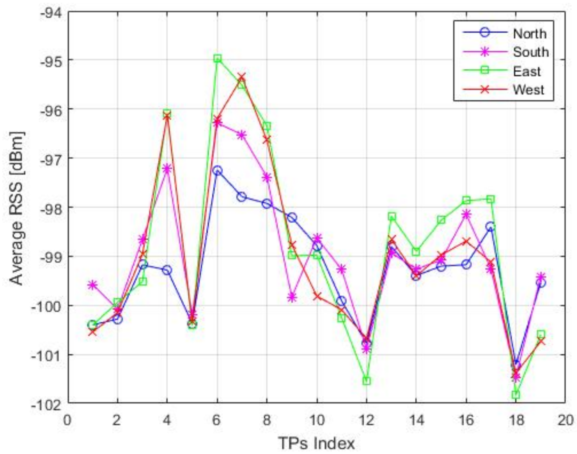

Figure 4.6 Approach II (TP set)

Figures highlight a quite obvious result: from a global environment point of view the orientation impact on the signal propagation is nearly negligible. This is due in particular to the fact that it is not possible to identify a particularly favorable orientation. Approach I underlines that given an AP the orientations that are favorable for a set of RP (TP) will be unfavorable for the remaining RPs (TPs) and viceversa. In conclusion, the average on the RPs will lead to similar RSS values. On the contrary, approach II underlines that given an RP (TP) the orientations that are favorable for a set of AP will be unfavorable for the remaining APs and viceversa. In conclusion, the average on the APs will lead to similar RSS values.

The results of the first experiment lead us to focus on a single AP, taken as a reference AP, placed in a known position (as indicated in Figure 4.1), in order to derive a more significant analysis.

The knowledge of the AP position allows to firstly sort the RPs from the nearest to the farthest and then discriminate them with respect to the presence/absence of user's body for each AP-RP direct path (referred in the following to as LOS/NLOS conditions). Given the area planimetry, the AP/RPs positions and the device antenna position, the LOS (or NLOS) condition is verified in two out of four orientations, strictly depending on the RP positions.

By following the above observations and given the reference AP, the RPs databases, previously organized in four different orientations as already discussed at the beginning of this section, have been now re-organized dependently on the LOS/NLOS condition. Figures 4.7, 4.8, 4.9 and 4.10 show the experimental results obtained by comparing these two different situations, in terms of RSS measured from the reference AP in each RP. Note that in order to clarify the analysis two groups of orientations have been studied: North/South on one hand, and East/West on the other hand.

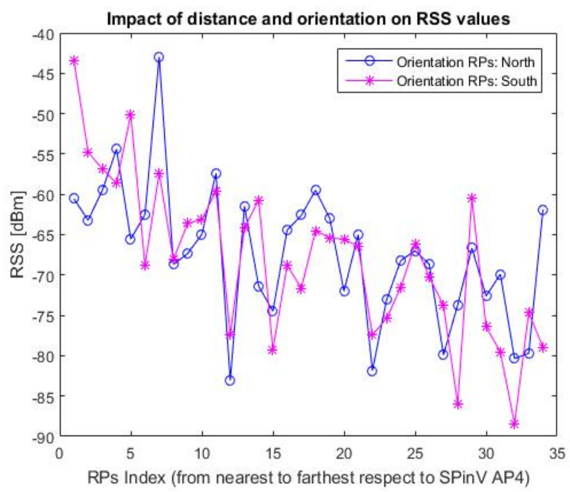

Figure 4.7 RSS values for all the RPs from a reference AP: orientations North and South

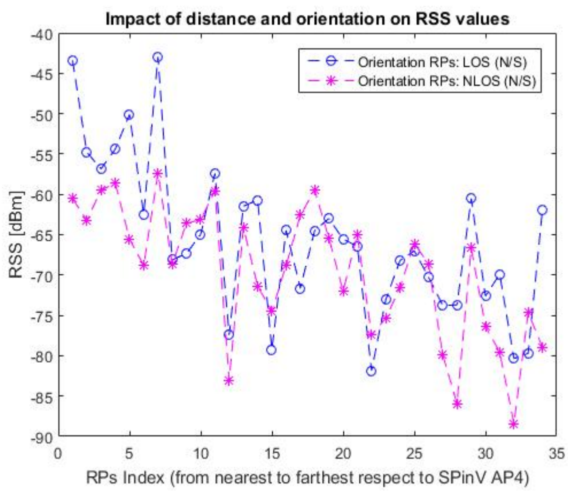

Figure 4.8 RSS values for all the RPs from a reference AP: conditions LOS/NLOS for orientations North and South

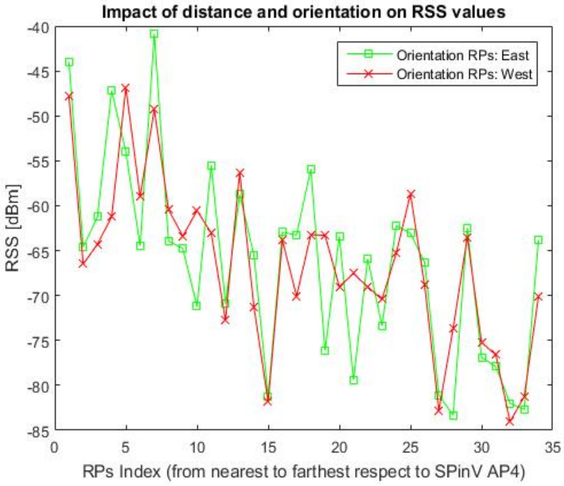

Figure 4.9 RSS values for all the RPs from a reference AP: orientations East and West

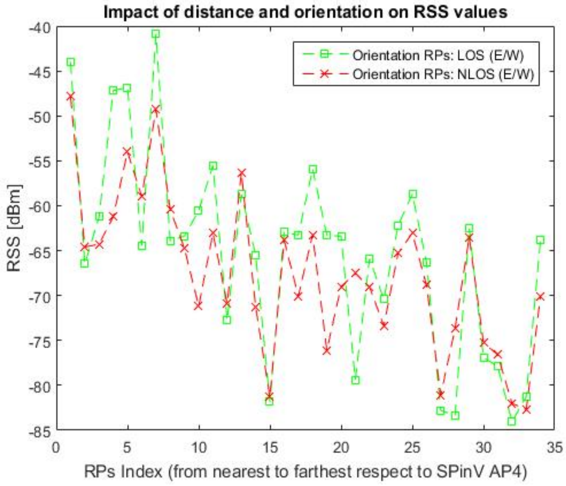

Figure 4.10 RSS values for all the RPs from a reference AP: conditions LOS/NLOS for orientations East and West

Table 4.1 [dB]

$\lvert \boldsymbol{North - South} \rvert$	0,5807
$\lvert \boldsymbol{LOS(N/S) - NLOS(N/S)} \rvert$	3,9597
$\lvert \boldsymbol{East - West} \rvert$	0,3167
$\lvert \boldsymbol{LOS(E/W) - NLOS(E/W)} \rvert$	2,2400

Figures and Table 4.1, that reports the difference between the average RSS values for each curve, clearly show that the difference between the measured RSS values is more significant when the RPs are considered in the LOS/NLOS conditions respect to the different orientation ones. This suggests that, given one AP, the presence/absence of the user's body in the direct path has a not negligible impact on the RSS value perceived in one RP.

The previous results can be confirmed by furtherly dividing the RPs respect to their positions in the environment. In particular, in the following experimental analysis the environmental obstructing objects in the direct path between the AP and the RPs have been taken into account; this led us to divide the RPs into 3 categories:

- Category I – zero walls LOS/NLOS: for the RPs belonging to this category the LOS/NLOS condition is just given by the absence/presence of the user's body because no walls are present in the AP-RPs direct path. Note that, given the reference AP position, the category I RPs are the ones taken in the corridor.

- Category II – one wall LOS/NLOS: the RPs belonging to this category are the ones that present one wall in the direct path; in particular "one wall LOS" means that the user's body is not present, while "one wall NLOS" considers the user's body.
- Category III – two walls LOS/NLOS: the RPs belonging to this category are the ones that present two walls in the direct path; in particular, "two walls LOS" means that the user's body is not present, while "two walls NLOS" considers the user's body.

Figures 4.11, 4.12 and 4.13 show the results obtained for Categories I, II, and III respectively. Moreover, Table 4.2 shows the average RSS for all categories and, for each category, the difference between the LOS and NLOS conditions.

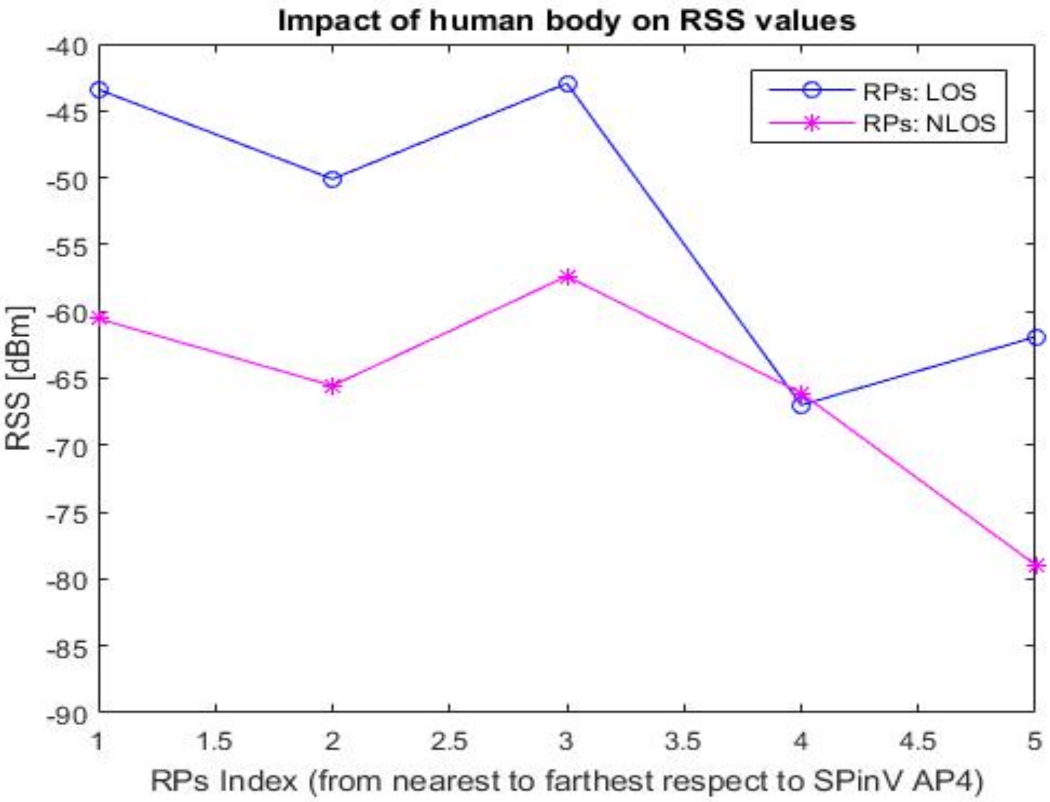

Figure 4.11 RSS values for the Category I RPs

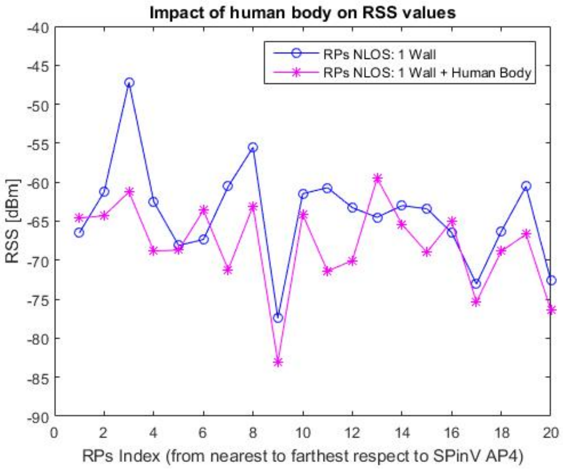

Figure 4.12 RSS values for the Category II RPs

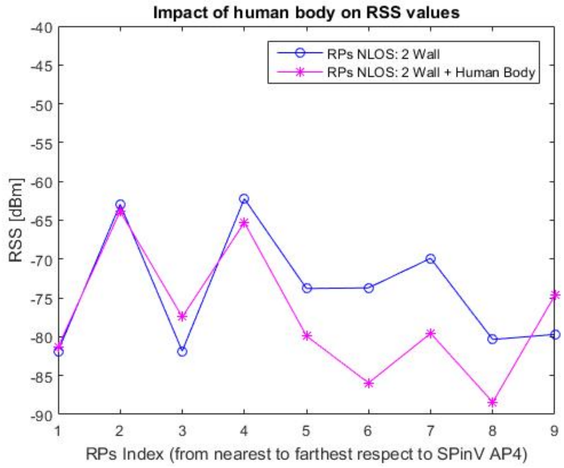

Figure 4.13 RSS values for the Category III RPs

Table 4.2 Average RSS values for each RP Category

Category	I	II	III
LOS [dBm]	-53.1	-64.1	-74.0
NLOS [dBm]	-65.7	-68.0	-77.4
$\boldsymbol{|LOS - NLOS|}$ **[dB]**	12.6	3.9	3.4

Both figures and Table 4.2 clearly suggest that the impact of user's body is highly significant for the Category I RPs and decreases for both Categories II and III, given that the blocking effect of human body is partially covered by the further attenuation introduced by the walls.

4.2 Impact of orientation on positioning accuracy

In this section the results of the experimental analysis on the achievable accuracy for the IPS implemented at the DIET 2nd floor are presented. In particular, the different analysis have been carried out in order to find the optimal application for the oriented databases taken during the offline phase.

The first experiment has been focused on understanding how the matching/mismatching of RP/TP databases affects the achievable positioning accuracy. For this reason, the four RP databases have been separately applied to each

TP database and for each TP the positioning error ε and the average positioning error $\bar{\varepsilon}$ have been evaluated as follows:

$$\varepsilon = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2} \qquad (1)$$

$$\bar{\varepsilon} = \frac{\sum_{i=1}^{N_{TP}} \varepsilon_i}{N_{TP}} \qquad (2)$$

where (x, y) indicates the real TP position while $(\hat{x}, \hat{y})$ indicates the estimated position. A W3NN with the Euclidean distance has been used for the estimation phase.

Figures 4.14, 4.15, 4.16 and 4.17 report the CDF of ε as a function of the selected TP database for each RP database while Table 4.3 reports the average errors $\bar{\varepsilon}$. Figures clearly show that ε is significantly affected by the selected TP/RP combination of databases; moreover, Table 4.3 show that $\bar{\varepsilon}$ is nearly minimized when the RP/TP databases matching is verified (values in red color). This general rule is not verified only for the West orientation, that also reports the worst performance accuracy respect to the other ones.

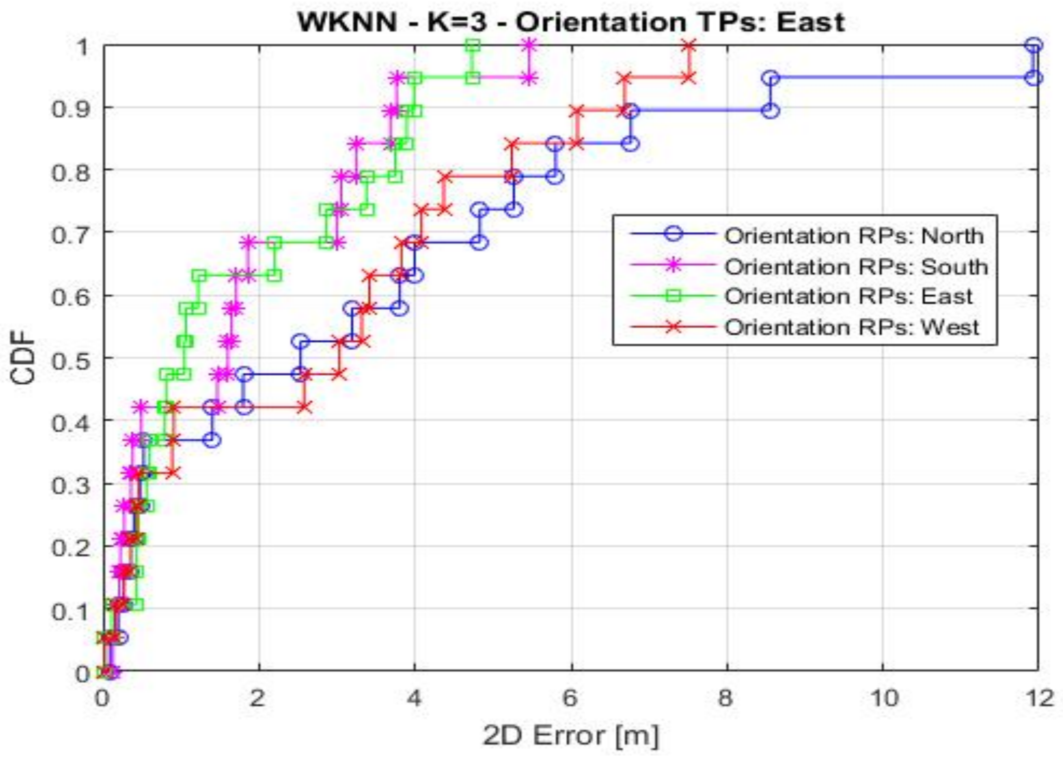

Figure 4.14 CDF of ε for TPs orientation East and all the RP orientations

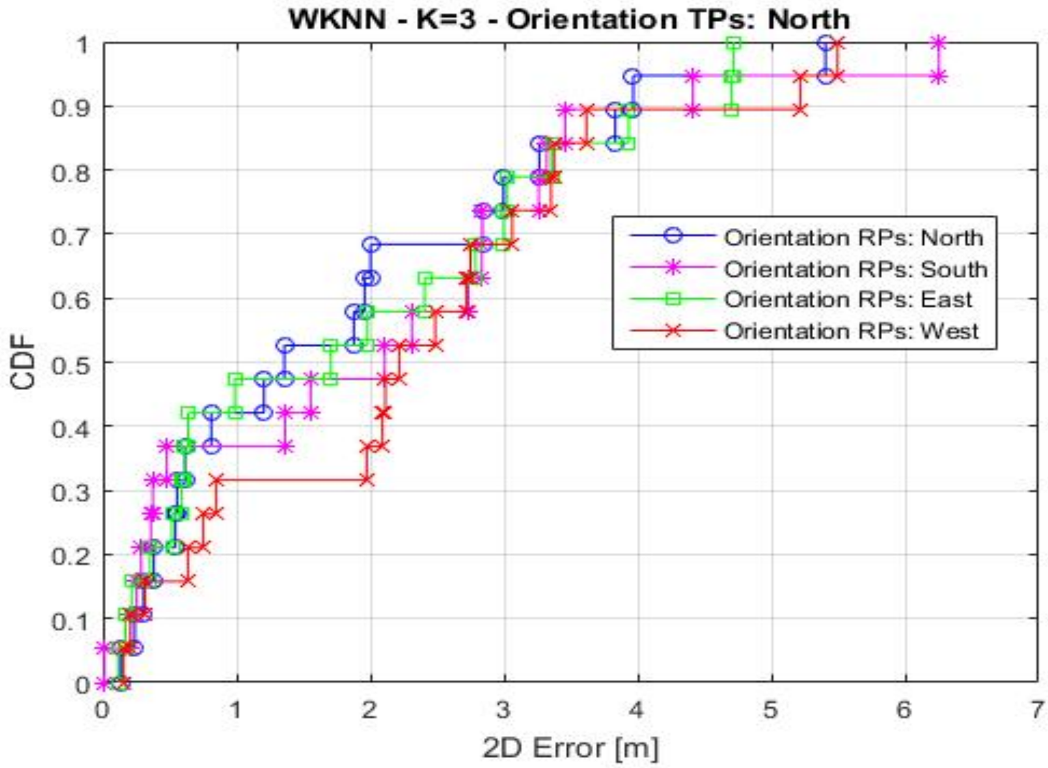

Figure 4.15 CDF of ε for TPs orientation North and all the RP orientations

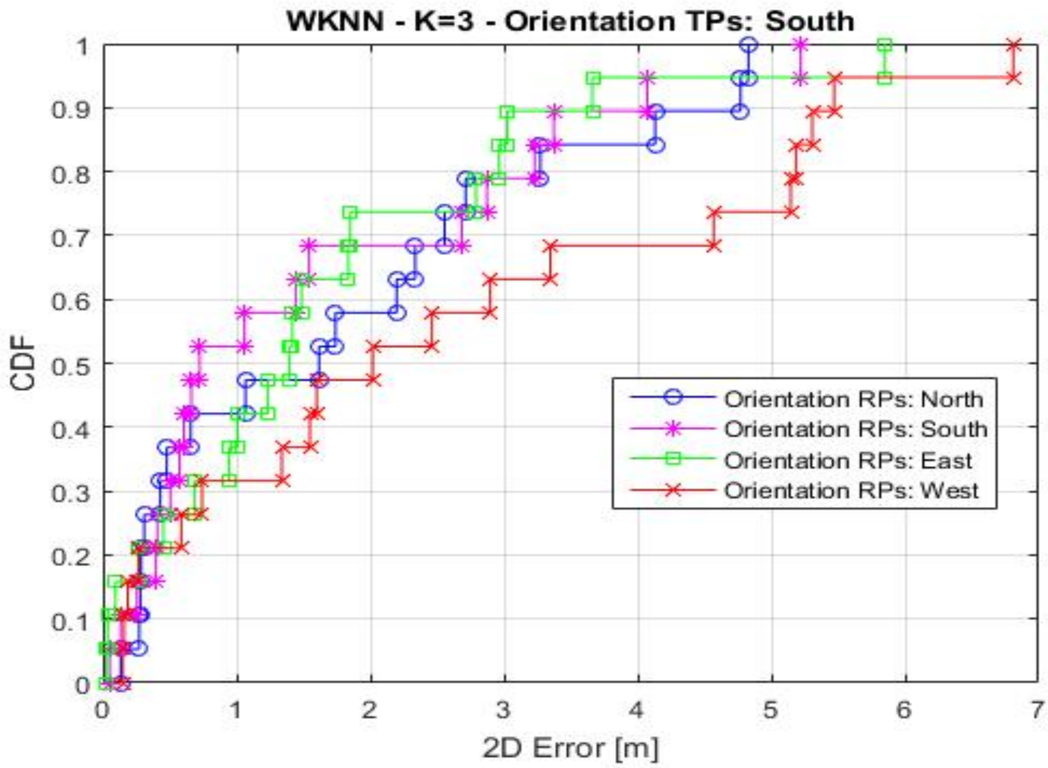

Figure 4.16 CDF of ε for TPs orientation South and all the RP orientations

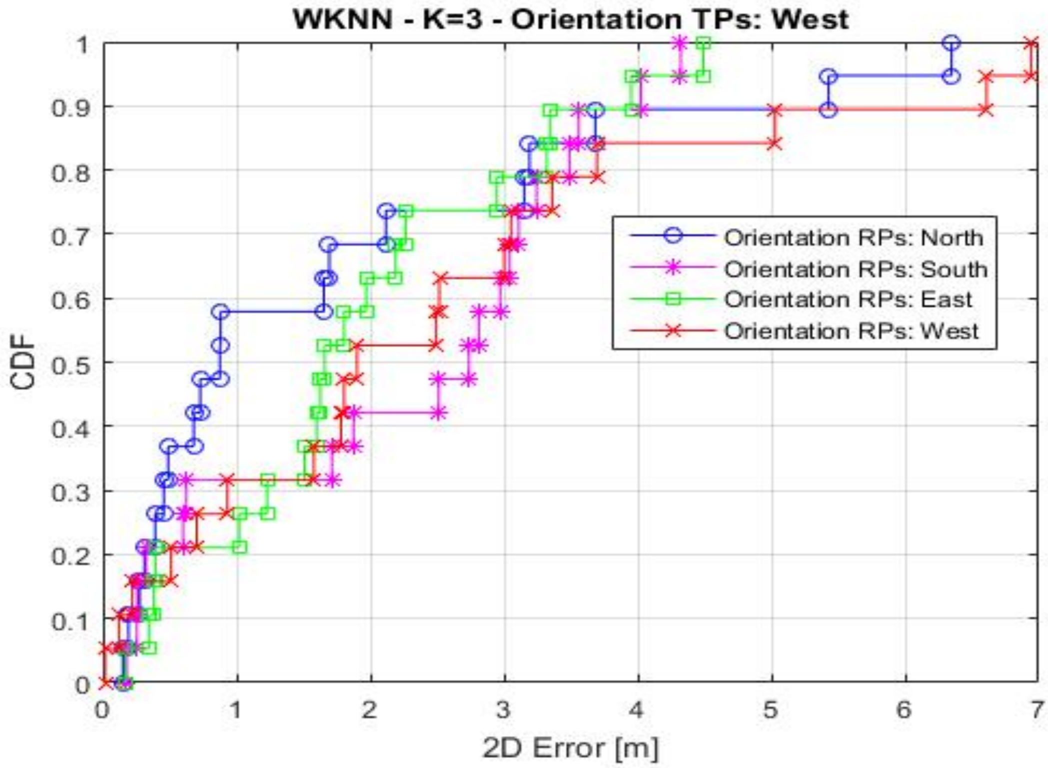

Figure 4.17 CDF of ε for TPs orientation West and all the RP orientations

Table 4.3 Average error $\bar{\varepsilon}$ for all TP/RP combinations

	TPs North	**TPs South**	**TPs East**	**TPs West**
RPs North	1.8	1.8	3.3	1.7
RPs South	2.0	1.6	1.7	2.2
RPs East	1.9	1.6	1.7	1.9
RPs West	2.3	2.6	2.8	2.4

The RP/TP databases matching can be done only if the target device orientation is known or reliably estimated. In case the target device orientation is unknown an optimal strategy for using the RP databases should be defined. Three different strategies can be highlighted:

- Strategy I – random selection: In this strategy only one RP database is used independently on the target orientation.

- Strategy II – no selection: In this strategy all the RP databases are separately used independently on the target orientation.
- Strategy III – average selection: In this strategy all the RP databases are used in order to create a new database generated as the average of the RSS values in the initial databases.

Figure 4.18 and Table 4.4 report the experimental result obtained by applying the previous strategies on the total set of TPs that is $N_{TP} \times O$. As a final result one can observe that strategy III leads to the minimum positioning error that is on average equal to 1.7 m.

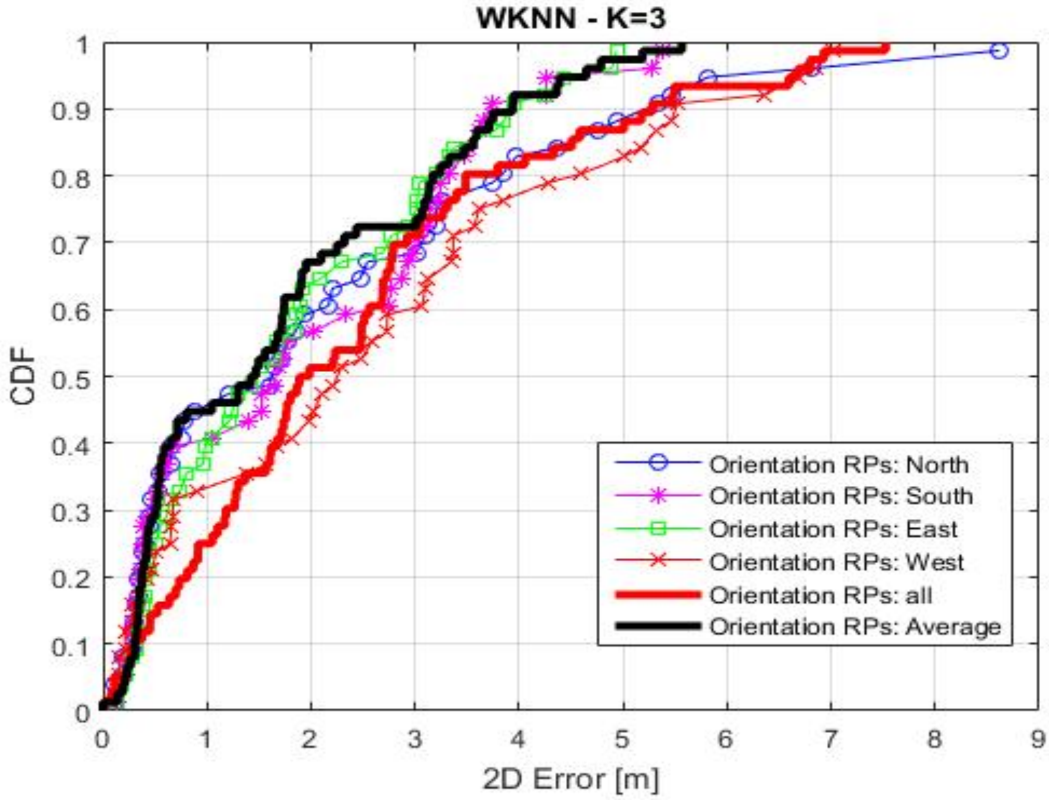

Figure 4.18 CDF of ε for Strategy I (North, South, East and West), Strategy II (all) and Strategy III (Average)

Table 4.3 Average error $\bar{\mathcal{E}}$ for Strategy I (North, South, East and West), Strategy II (all) and Strategy III (Average)

Strategy I				**Strategy II**	**Strategy III**
North	*South*	*East*	*West*	*All*	*Average*
2.2	1.9	1.8	2.6	2.4	1.7

CHAPTER 5
CONCLUSIONS AND FUTURE WORK

In this work an experimental analysis of the impact of user/device orientation on the achievable accuracy of a WiFi fingerprinting IPS is reported. After reporting related work and main results on the same topic, the work shows experimental results obtained at the DIET Department of Sapienza University of Rome. Within this environment a real kNN/WkNN-based IPS has been deployed and several experiments regarding the impact of user/device orientation have been carried out.
When focusing on the impact of orientation on signal propagation, experimental results have shown that the orientation has a negligible effect when other variability factors, such as presence of obstructing objects in the TX-RX direct path, are included in the analysis; in fact, it has been observed that a significant impact is only visible when no objects are present.
When focusing on the impact of orientation on positioning accuracy, experimental results have shown that, in the hypothesis of knowing the target device orientation, the positioning error is nearly minimized when the orientation matching between the RPs and the TPs is verified. Moreover, in the hypothesis of not knowing the target device orientation, the positioning error can be minimized by using as RP fingerprints the ones obtained by averaging the RSS values measured for each orientation.

Future work goes in the direction of extending the present framework to different analysis. In particular, the extension of the presented deterministic IPS to the probabilistic approach is under investigation together with the analysis of the impact of the device heterogeneity on the positioning accuracy.

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