Study for the Development of a Guidance and Information System Based on Wi-Fi for TU Wien

Alexander LEB, Guenther RETSCHER, Austria

Key words: Wi-Fi positioning, probabilistic fingerprinting approach, Mahalanobis distance, kinematic system training, continuous training, RSSI scan duration dependence

SUMMARY

A guidance and information system based on Wi-Fi signals using fingerprinting for localization is currently under development for the whole University campus of TU Wien (Vienna University of Technology). In a first step, the availability, performance, and usability of Wi-Fi in selected areas of the University are analyzed. For this purpose, Wi-Fi received signal strengths (RSS) of the surrounding access points (APs) were measured in front of the main building of the University, in the library and in a large multi-storey office building called Freihaus under real conditions. The measurements were carried out in static, kinematic and stop-and-go mode with six different smartphones. In this paper, the kinematic measurements of users walking along predefined trajectories are analyzed. Kinematic measurements, however, pose much greater challenges than the usual static or stop-and-go measurements. The analysis of the system training measurements showed that there are sufficiently stable signals available everywhere on the campus to carry out a position determination using Wi-Fi fingerprinting. A probabilistic fingerprinting approach based on the Mahalanobis distance was then applied. The resulting deviations from the ground truth in the positioning phase were in the range of 1 to 3 m in the Freihaus office building. A significant dependence of the results in the kinematic mode, however, is caused by the duration of a single Wi-Fi scan. The durations were in the range of 2.4 to 4.1 s depending on the used smartphone. This can result in different accuracies for kinematic positioning, as fewer measurements along the trajectories for interpolation are available for a device with longer scan duration.

KURZFASSUNG

Ein campusweites Führungs- und Informationssystem für die Technische Universität Wien soll durch die Nutzung von WLAN-Signalen und der Positionierungsmethode Fingerprinting realisiert werden. In einem ersten Schritt werden daher die Verfügbarkeit, Leistungsfähigkeit und Nutzbarkeit von WLAN in ausgewählten Bereichen untersucht. Für diesen Zweck wurden die WLAN-Signalstärken vor dem Hauptgebäude am Karlsplatz, in der Universitätsbibliothek sowie im Freihaus-Bürogebäude unter realen Bedingungen gemessen. Die Messungen wurden dabei statisch, kinematisch und im Stop-and-Go Modus mit sechs verschiedenen Smartphones durchgeführt. In diesem Beitrag werden die kinematischen

Messungen entlang von vordefinierten Trajektorien, die mit normaler Schrittgeschwindigkeit abgegangenen wurden, analysiert. Kinematische Messungen stellen jedoch eine wesentlich größere Herausforderung dar als die üblichen statischen bzw. Messungen im Stop-and-Go Modus. Die Analyse der Trainingsmessungen zeigte, dass genügend stabile WLAN-Signale campusweit für die Positionierung mittels Fingerprinting vorhanden sind. Für das Fingerprinting wurde ein probabilistischer Ansatz mit Berechnung der Mahalanobis-Distanz gewählt. Die ermittelten Abweichungen der berechneten Positionen zu den Sollwerten in der Positionierungsphase lagen im Freihaus-Gebäude bei 1 bis 3 m. Eine signifikante Abhängigkeit der Ergebnisse vom Smartphone zeigt sich jedoch bei den kinematischen Messungen durch die unterschiedliche Dauer eines einzelnen WLAN-Scans. Diese lag durchschnittlich im Bereich von 2,4 bis 4,1 s und kann damit zu unterschiedlichen Genauigkeiten für die kinematische Positionierung je nach verwendetem Endgerät führen, da bei einer längeren Scandauer weniger Messwerte entlang der Trajektorie für eine Interpolation zur Verfügung stehen.

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1. INTRODUCTION

TU Wien (Vienna University of Technology) is the largest scientific-technical research and education institution in Austria. With its four inner-city locations (main building at Karlsplatz, campus Getreidemarkt, Gußhaus and Freihaus) as well as a science center further away from the city center, the University has more than 12,000 rooms in 30 buildings on an area of approximately 269,000 m^2 available. With such a large number of buildings and rooms, a positioning and navigation system can be a helpful tool to orientate yourself on campus and in the surrounding city. The motivation of this study is therefore to help students, employees, and visitors of the University to find classrooms, offices, and other rooms as well as even bookshelves in the library with the help of a mobile device. Thus, the positioning and navigation system has to be integrated into the University's and the library's information system.

In recent years, a number of technologies and methods have been developed and improved for indoor positioning. One of these technologies is based on the use of Wireless Fidelity (Wi-Fi). As such infrastructure is already installed in most public buildings and therefore costs are low, it is one of the most researched technologies for indoor positioning. Thereby positioning can be made either cell-based, by lateration or fingerprinting. In particular, location fingerprinting has proven itself in practice. It is an approach from the field of pattern recognition and based on received signal strength indicator (RSSI) measurements of the surrounding Wi-Fi Access Points (APs) in an off-line training and an on-line positioning phase. During the training phase, the RSSIs of the surrounding APs are measured in the area of interest at reference points to built-up a fingerprinting database, which can be visualized by signal strength radio maps. For the positioning in the on-line phase, the measured fingerprint is then compared at an unknown location with those in the empirically determined radio map. Finally, the position in the radio map that best matches the on-line RSS measurement is returned. The radio map can also be created using a propagation model, which can be very complex. A disadvantage of the empirical method, however, may be the time required to set up and maintain the database. In addition, the measurements must be carried out again during the installation of a new transmitter or other structural changes. Another challenge is the large variation of the observed RSS values due to signal fluctuations (Retscher, 2020). Despite these disadvantages, fingerprinting is nowadays one of the most popular method for an indoor positioning system (see e.g. Chen et al., 2012; Liu et al., 2007).

The paper is structured as follows: In section 2 the test site and the measurement procedure are introduced followed by a discussion of the creation of the fingerprinting radio map in section 3. Section 4 presents an analysis of different scan durations of the employed smartphones and section 5 the major results obtained in the positioning phase for localization in kinematic mode. Section 6 discusses the major findings followed by conclusions and an outlook in section 7.

2. TEST SITE AND MEASUREMENT PROCEDURES

Training measurements were carried out in front of the main building at Karlsplatz, in the University library and the Freihaus building along predefined trajectories with reference waypoints at decision points, such as trajectory crossings, and at irregular intervals depending on the local conditions. During the kinematic measurements, a time stamp was set at the waypoints when the user passed, in order to be able to interpolate the RSSI at these points. The part of the trajectory with its waypoints on the second floor in the Freihaus building is shown in Figure 1. The trajectory has a length of about 243 m and starts in front of the main entrance leading to the offices and classrooms of our department. Outside the area of the department the distances between the selected waypoints are between 5 and 14 m. Since there are many offices in the area of our group, the waypoints are at shorter distances between 3 to 6 m in front of each office along the corridor. The users walked along the trajectories with an average walking speed of 1 ms^{-1} in both ways back and forth taking around 4 minutes for the whole trajectory. Apart from measurements in kinematic mode, also stop-and-go and static observations were carried out along the trajectory and on the waypoints. For the analyses, also cells (denoted with blue Roman numbers in Figure 1) were defined consisting of different numbers of waypoints in dependence of the local conditions. Six APs on the ground floor and 41 APs on the entire second floor can be sensed. In the whole area, a total of 136 stationary APs were observed, of which 82 were from the two University networks. One of these is the communication network from the University (TUnet) and the second the so-called Geosensor network of our group; both having different hardware for the APs.

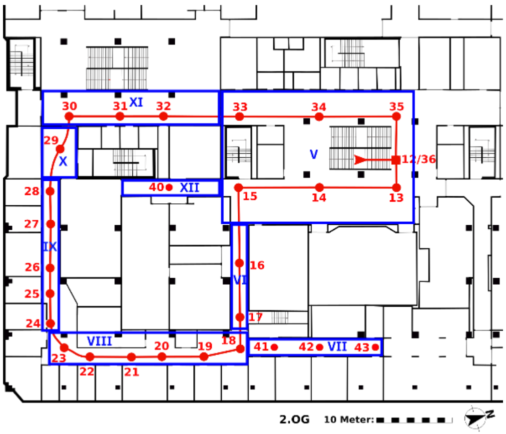

Figure 1. Waypoints and segmented cells on the second floor in the Freihaus building

When considering the availability of the Wi-Fi signals in the Freihaus building (see Figure 2), the difference between the ground and second floor is obvious. At waypoints 3 to 10 and 37 to 39 located on the ground floor, significantly fewer Wi-Fi signals are received per scan than at the waypoints located on the second floor. In this area, sufficient signals can be sensed in order to be able to perform fingerprinting in a meaningful way. On average, 46 stationary TUnet signals per scan were measured in the building. It is also visible in Figure 2 that the difference between all signals and the ones from the TUnet is greatest at those waypoints located in front of the building (waypoints 1 and 2) as more other APs not belonging to the University networks are visible.

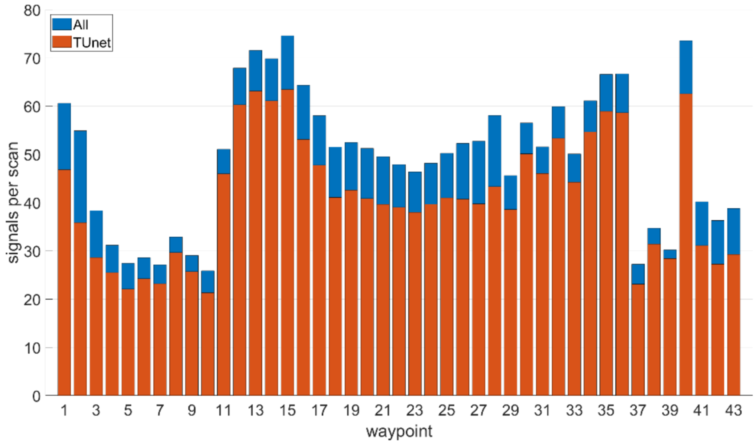

Figure 2. Average number of signals per scan on all trajectory waypoints

3. CREATION OF THE FINPRINTING RADIO MAP

In order to know the RSSIs and variances of the APs not only at the waypoints, but also in the whole test site, an area-wide interpolation is carried out for each AP for both the RSSI values and the variances. Different interpolation methods can be used for this purpose (see e.g. Retscher and Leb, 2019). An interpolation by natural neighbours, also referred to as Voronoï interpolation, is used in this work (Ledoux and Gold, 2005; Lee and Han, 2012; Üreten et al., 2012). The grid width of the interpolated radio maps is set to 1 m, which results in that positioning can be carried out within meter accuracy. As examples, Figure 3 shows the radio maps of two APs, one from the Universities communication network TUnet and one from the Geosensor network for the 2.4 and the 5 GHz frequency bands. As can be seen, the different frequency band of the signal shows a significant influence. Although the two APs are only 1 m apart, the AP of the Geosensor network has a greater range and is also more strongly received at all waypoints. For example, the RSSI of this AP at waypoint 28 is almost 31 dBm stronger than the other AP of TUnet. The reason for this large difference is due to the hardware of the AP, since the AP from the Geosensor network come from a different manufacturer (D-Link) than those from TUnet (Cisco systems). With the 5 GHz signal, however, the difference is no longer quite as large, but still amounts to almost 13 dBm at waypoint 28. Another important finding in the investigation of the radio maps is that the database created either from static, stop-and-go and kinematic measurement methods have a high similarity in both RSSIs and variances. For future work, this also means that continuous system training can be carried out, which means that the training phase is much shorter.

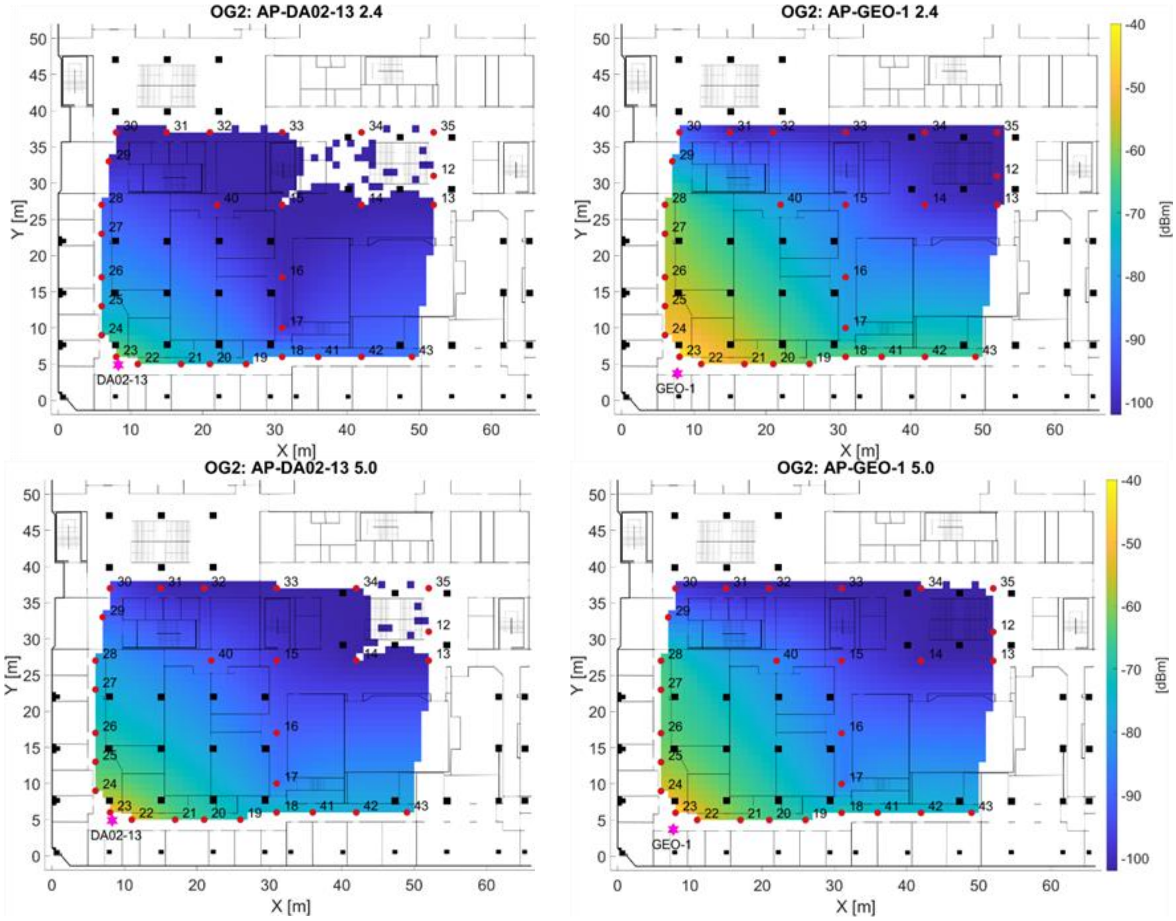

Figure 3. Radio maps of the 2.4 GHz (above) and 5 GHz (below) frequency bands for the AP DA02-13 from the University network (left) und GEO-1 from the Geosensor network (right)

4. ANALYSIS OF DIFFERENT SCAN DURATIONS

Figure 4 shows RSSI time series for two smartphones in a kinematic measurement run. Every smartphone needs a certain amount of time to perform a single Wi-Fi scan. These can be very different in length, as has been the case with the six different devices used (see Table 1). In Figure 4, therefore, the series of the two smartphones with the shortest and longest scan duration are shown. Although more scans along the trajectory can be performed with the OnePlus 5T smartphone than with the Sony Z3 due to shorter scanning duration (201 versus 115 scans), a high similarity between the two-time series can be observed with a correlation coefficient of 0.96. But for kinematic positioning in the on-line phase, the scan duration has a significant influence, as shown in the following. In some kinematic measurements, it was found that individual scan durations sometimes deviate too much from the average scan durations. Figure 5 shows such irregular scan durations. It can be seen that, among other things, the Sony Z3 has some longer scanning times of approximately 15 seconds. The Nexus 5X, on the other hand, performs many scans with a measuring time of only a few milliseconds. These irregular scanning times are examined in more detail below.

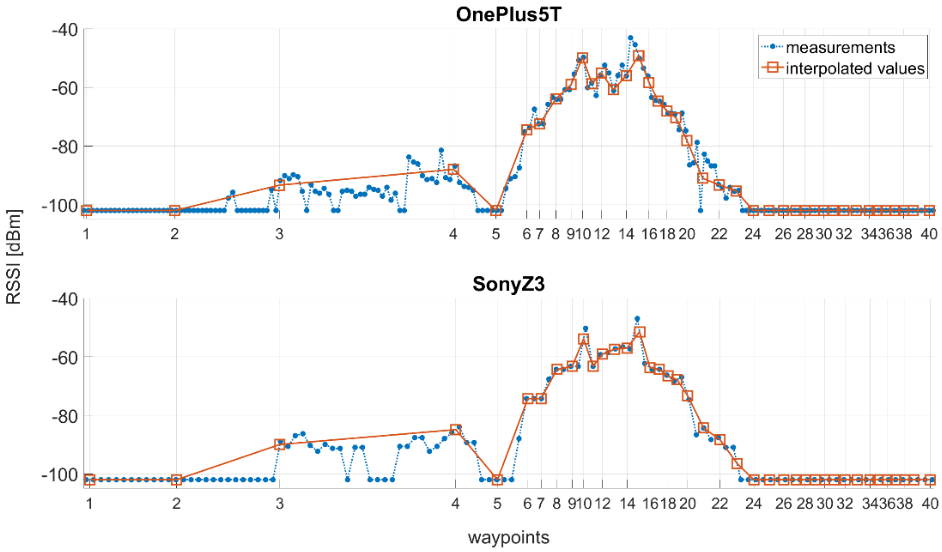

Figure 4. RSSI series along the trajectory in the Freihaus building for two smartphones

smartphone	scan duration [s]
Nexus 5X	3.8
OnePlus 5T	2.4
Samsung S3A	3.5
Samsung S3B	3.5
Samsung S7	2.5
Sony Z3	4.1

Table 1. Average scan duration of the six employed smartphones

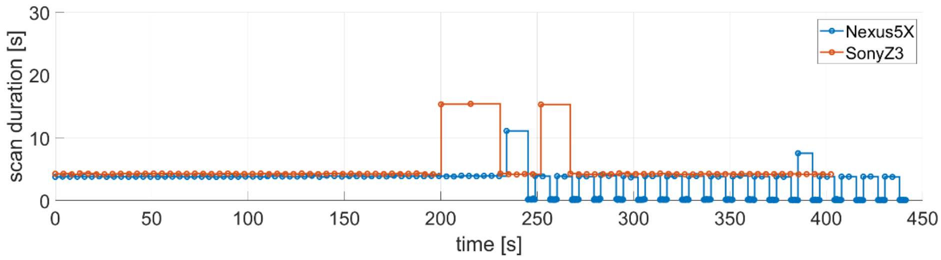

Figure 5. Irregular scan durations of the two smartphones Nexus 5X and Sony Z3

The short scan durations of the Nexus 5X are shown in Figure 6 together with the measured signal strengths. The RSSI are from the 5 GHz signal of the same AP as in Figure 4. As shown in Figure 6 (top), the irregular scanning periods begin between waypoints 6 and 7. The pattern is always the same: first a slightly longer scan occurs, then a series of scans with a short scan duration, whereby the total duration of these scans corresponds to the average scan duration. Then follow two scans with a normal scan duration and finally a series of short scans begins. The reason for this could not be clarified and was only found with the

Nexus 5X. The problem with this is that during these short scans the RSSI values do not change, which does not correspond to the reality. For this reason, the scans were eliminated with a short measurement duration, which, however, results in a scan gap from one scan (see Figure 6 (below).

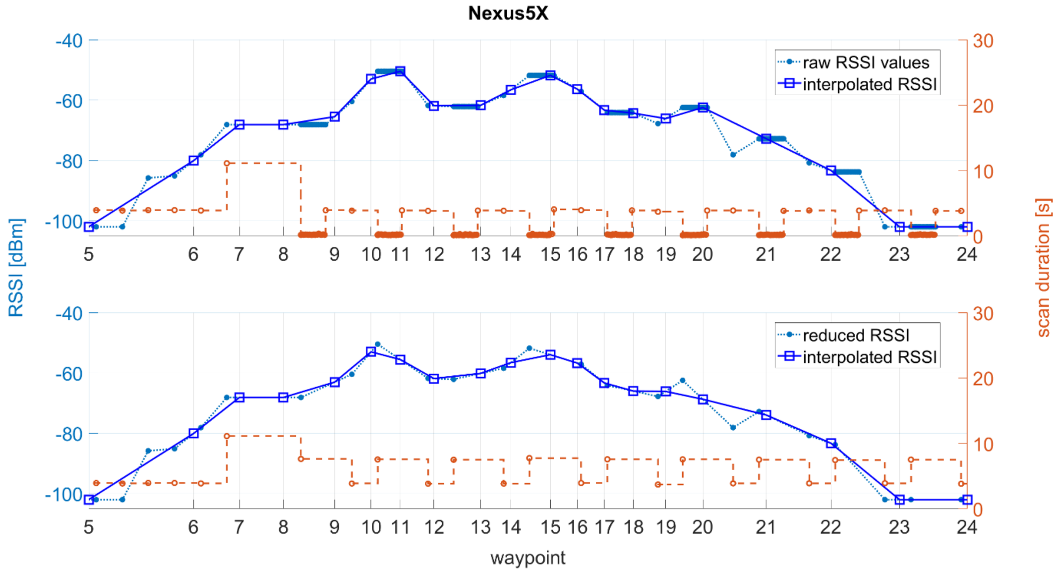

Figure 6. Kinematic measurements with short scan durations

The three longer scan durations of the Sony Z3 are shown enlarged in Figure 7 together with the Samsung S3A, which performed the measurement at the same time. As can be seen, the Sony Z3 is located near waypoints 7, 9 and 16 for longer scanning times of approximately 15 seconds, which means that no Wi-Fi scan was performed at an average walking speed of 1 ms^{-1} along 15 m. Therefore, no Wi-Fi scans are performed near waypoints 8, 10, 11, 17 and 18. In this case, the interpolation still provides approximately the same values as with the kinematic measurement with the Samsung S3A. However, this does not occur in general. If, for example, no Wi-Fi scans were carried out between waypoint 11 and 14, the interpolation would estimate too high RSSI values for the waypoints in between. The reason for the above-average length of time is that the smartphone, if it is not connected to any Wi-Fi network, automatically tries to connect to known networks. This connection trial can also take longer, which means that the Wi-Fi scan is performed longer. Therefore, the measurements on each smartphone should deactivate the automatic Wi-Fi connection for each network. Now one can ask the question, how long the maximum scanning time may be, so that an interpolation is still meaningful. If there is a longer scan time between two waypoints, which are far apart, then the longer scan time does not have any influence on the interpolation. The maximum possible scanning time therefore depends on the distance between the waypoints respective the spatial conditions. If two waypoints are close together, it can be assumed that the signal is similarly strong. If they are several meters apart, the RSSI values can vary significantly depending on the spatial environment and the interpolation may no longer provide meaningful values. Therefore, in kinematic off-line training measurements, care must be taken whether and where longer scanning times occur. The smartphone should always perform a scan in the immediate vicinity of each waypoint. Since the fingerprint database in this work consists of many scans and these irregular scan durations only occurred in a few measurement runs, these scanning delays have no significant effect on the positioning results. If a long scan occurs in the on-line positioning phase, it is clear that no positioning can be carried out during this time, as no Wi-Fi signal strengths are available.

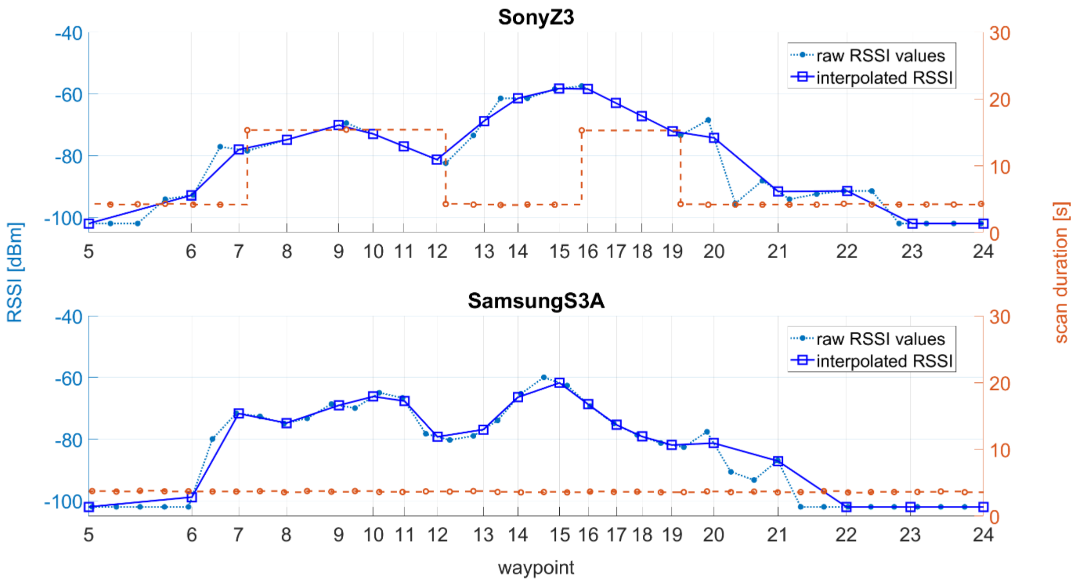

Figure 7. Kinematic measurements with long scan durations

5. POSITIONING PHASE FOR KINEMATIC MEASUREMENTS

For fingerprinting in this work, a probabilistic approach based on the calculation of the Mahalanobis distance is applied. The derivation of this approach can be found e.g. in Yeung et al. (2007). It is based on Bayesian filtering where Bayes' theorem (see e.g. Gordon et al., 1993; Koch, 2000) is employed. A posterior probability density function (PDF) can be calculated because of the fact that the fingerprints contain information about the signal characteristics. The Mahalanobis distance d^M has the form:

$$d^M\left(\boldsymbol{f}_{map}^i, \boldsymbol{f}_{obs}\right) = \left(\boldsymbol{f}_{obs} - \boldsymbol{f}_{map}^i\right)^T \boldsymbol{C}_{ff_{map,i}}^{-1}\left(\boldsymbol{f}_{obs} - \boldsymbol{f}_{map}^i\right) \quad (1)$$

where $\boldsymbol{f}_{obs}$ is the assigned RSSI measurement to a position $\boldsymbol{f}_{map}^i$ in the radio map and $\boldsymbol{C}_{ff_{map,i}}$ its empirical covariance matrix.

As the inverse of the covariance matrix is the weight matrix, the weighted square sum of the RSSI differences (between off-line training and on-line positioning phase) is calculated for the Mahalanobis distance. Then the weights are inversely proportional to the variances of the corresponding fingerprints. If the covariance matrix is the unit matrix, the Mahalanobis distance d^M corresponds to the Euclidean distance, which is most commonly used in the deterministic fingerprinting approach (see e.g. Honkavirta et al., 2009; Moghtadaiee and Dempster, 2015). A large number of studies, however, have shown that probabilistic fingerprinting offers a higher accuracy than the deterministic approaches in indoor positioning, as they take better account of signal fluctuations. This is why the Mahalanobis distance is used here in this work.

The Figures 8 show two estimated trajectories of the best and worst measurement run. It is evident that the positions have been determined in the correct order and that the resulting trajectories can be reconstructed well. The deviations of the estimated positions from the ground truth in the kinematic measurements are in the range of 0.8 to 2.6 m and amount to 1.6 m on average; the median is only 1.0 m. The biggest deviations occurred with the smartphone Sony Z3 with a median of 2.5 m and a maximum value of 10.0 m. This is due to the longer duration for a single RSSI scan (4.1 s on average; compare Table 1). The results of the Samsung S7 smartphone with a scan duration of 2.5 s show on average the smallest median of only 1.0 m.

The maximum deviation of 11.0 m occurred at waypoint 20 for the Samsung S3B smartphone in all runs. In Figure 9, the position determination for this waypoint is analyzed by displaying the calculated Mahalanobis distance for the measurements. For the first, more precise measurement (Figure 9 above), the calculated position is 5.0 m away from the ground truth. The difference in the Mahalanobis distance between the true and the estimated position is approximately 8 dBm. In the second, more inaccurate result (Figure 9 below), the position is determined too far to the right as at the true location the calculated Mahalanobis distance is 111.6 dBm and at the estimated position 52.3 dBm. In summary, it can be said that in general in the Freihaus building the position on each waypoint can be well determined, which is due to the high number of visible APs.

6. DISSCUSSION OF THE MAJOR FINDINGS

The aim of this work was the development of a campus-wide positioning system at TU Wien with an emphasis on the indoor areas. Indoor positioning poses a number of challenges, especially in large and complex buildings. For example, several effects such as signal attenuation signal fluctuations, interference and multipath play a decisive role in signal propagation. The RSSIs, the SSIDs (Service Set Identifier) and the associated MAC (Media Access Control) addresses of the Wi-Fi signals can be retrieved without an authenticated connection and are thus freely available. This has the advantage that positioning can be carried out autonomously at the users' side, thus avoiding data protection concerns that typically occur with other positioning technologies. For positioning using Wi-Fi fingerprinting, it is essential that there are sufficient APs in the building and that they are well distributed throughout the building. An initial analysis showed that there are sufficient signals at each reference point in the selected measuring area.

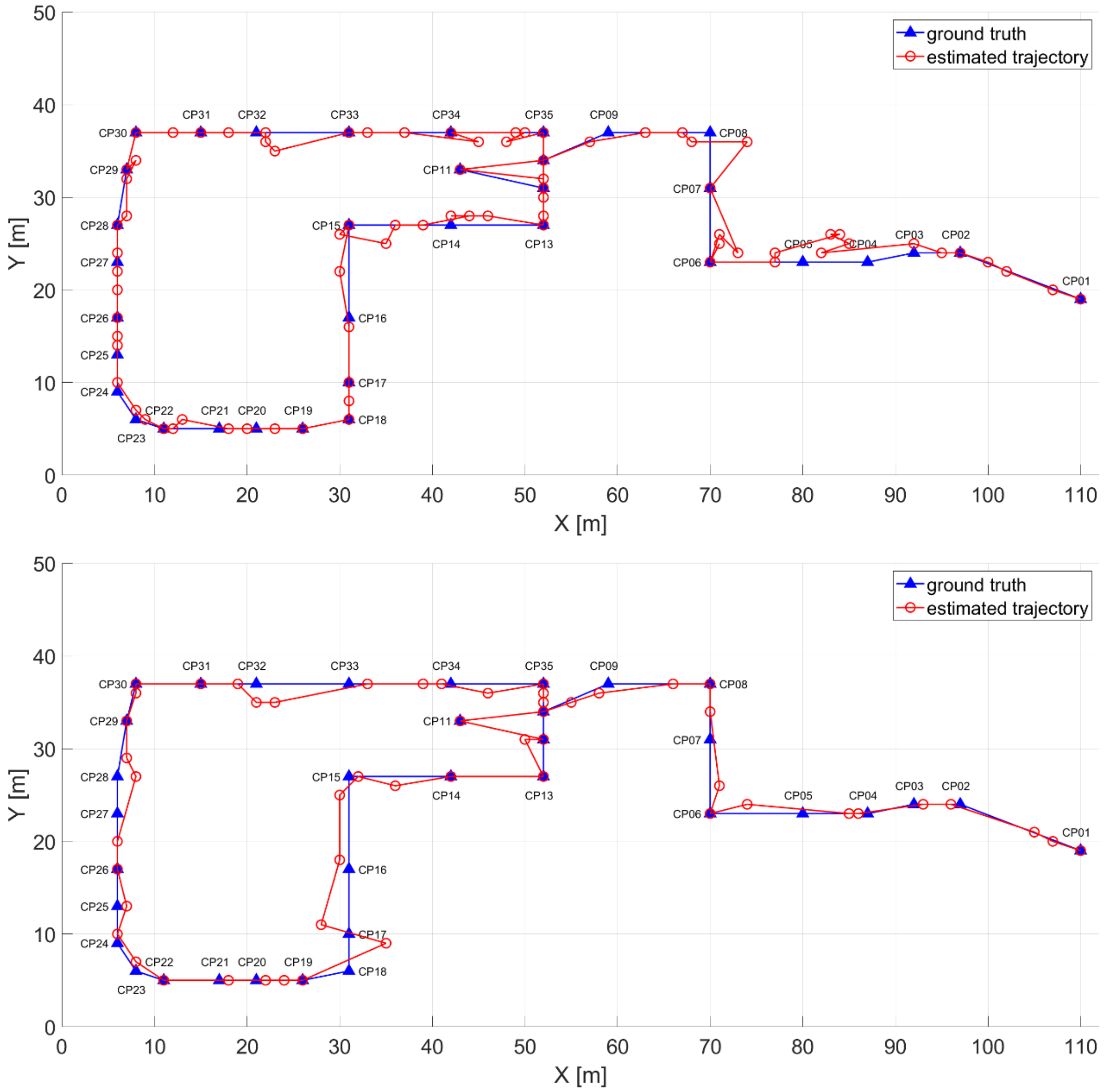

Figure 8. Kinematic positioning result with the Samsung S7 (above) and the Sony Z3 (below)

A long-term measurement showed large temporal variations in signal strengths and signal noise. It was found that fluctuations of up to ±5 dBm can occur during the day. At night, the signals are much more stable. The greater the number of people in the building, the greater the variation in the signals. One reason for this is the multipath effect caused by short-term obstacles (people or even opening or closing of doors, etc.) and, on the other hand, the dynamic transmission power of the APs which also depends on the number of Wi-Fi users. Measurements in different orientations have also shown that the human body can greatly weaken the Wi-Fi signal when it is between the smartphone and the AP. It is interesting to note that the attenuation on the 5 GHz frequency band is slightly stronger than on that of the 2.4 GHz band. For this reason, the off-line measurements on a reference point were always carried out in several orientations (mostly in all 4 or in 2 in the possible direction of movement), which enabled the influence of the human body to be reduced.

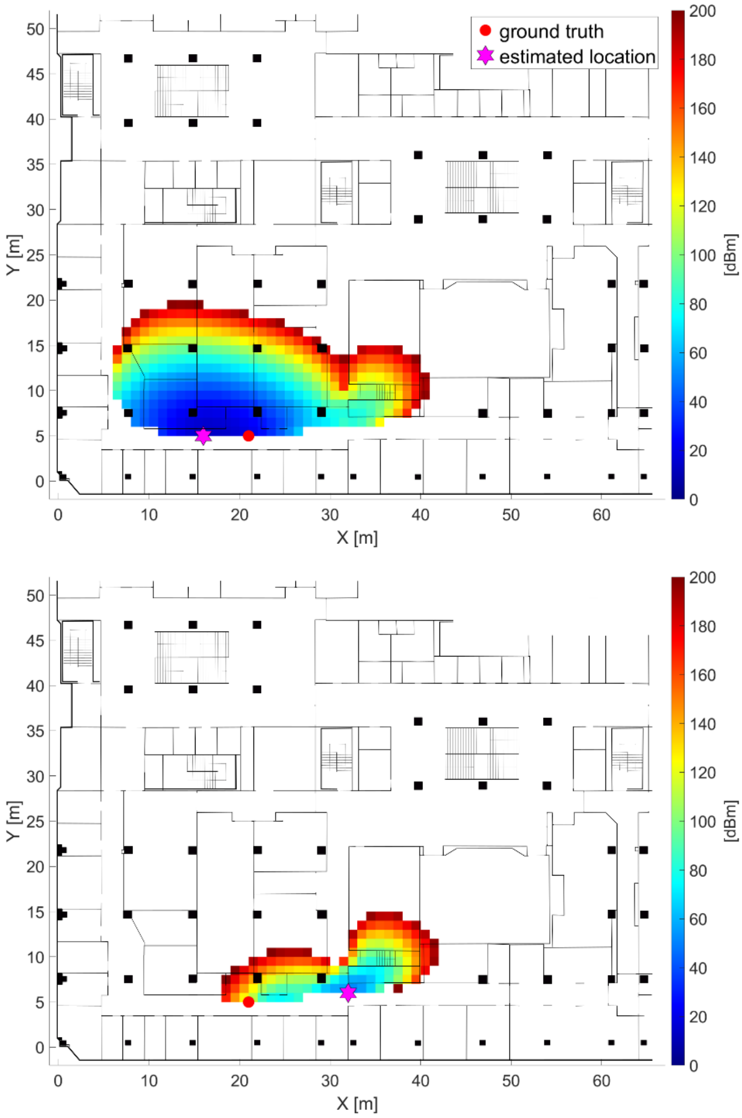

Figure 9. Mahalanobis distances for two results obtained with the Samsung S3B on waypoint 20

For the time being, the off-line measurements were stored separately for static and kinematic measurements in separate databases. To compare these measurement methods and databases, the differences in the mean signal strengths were calculated for each checkpoint and access point. In addition, the correlation coefficient between pairs of the same APs was calculated. On the one hand, the database with the averaged RSS values was used and, on the other hand, their variances. The mean correlation coefficients and differences between the databases are shown in Table 2. In terms of RSS values, the databases hardly differ and show a high correlation with another. The mean difference between pairs of the same APs is also very low. For the variances, the correlation with the kinematic measurements is slightly weaker. This is probably due to the lower number of off-line measurements (60 scans per checkpoint) with this observation method. All in all there are no significant differences between the databases, which is why the databases were combined for the subsequent creation of the radio maps and position determination. This means that kinematic training measurements can be used similar to static measurements. Their advantage is that the time required for building-up the database is much less.

	RSSI		variances	
	$\bar{r}$	$\bar{d}$ *[dBm]*	$\bar{r}$	$\bar{d}$ *[dBm]*
static – kinematic	0.95	0.4	0.88	3.9
static – stop-and-go	0.99	0.3	0.96	2.6
kinematic – stop-and-go	0.95	0.4	0.88	4.0

Table 2. Mean correlation coefficient ($\bar{r}$) and difference ($\bar{d}$) between the databases

When looking at the visibility of the APs at various waypoints, it was found that the greater the signal strength of an AP, the more often this AP is also visible. When viewing the radio maps, it was also found that the range of a Wi-Fi signal depends on the location and design of the AP as well as on the spatial situation. Furthermore, the frequency band also plays a decisive role.

The Mahalanobis distance, i.e., the distance between on-line and off-line fingerprint, was used to determine the position of the user. Ideally, the Mahalanobis distance near the correct location is very short and increases with distance. This means that the position with the shortest distance is the location searched, i.e., the nearest neighbour. In a further step, it was examined whether the position determination improves when several neighbours (kNN neighbour method) are used. However, there has been no significant improvement in the study area. The determined Mahalanobis distance could also serve as measure of integrity. If the Mahalanobis distance exceeds a certain value, then the calculated result is invalid, and a new scan must be performed.

The trajectories were reconstructed very well with deviations of the estimated positions from the ground truth in the range of 1 to 3 m. A dependence on the results is seen caused by the different scan duration of the devices. Those smartphones with the longest scanning time have achieved the lowest accuracy. This is due to the necessary interpolation between the Wi-Fi scans in the kinematic measurements. If a calibration of the different smartphones is performed, the device-dependent sensitivity is reduced.

7. CONCLUSIONS AND OUTLOOK

The investigations at TU Wien have shown that Wi-Fi fingerprinting can be used to achieve positioning with meter accuracy with the already available hardware for the APs. A further increase is expected if additional hardware is deployed, such as cost-effective Raspberry Pi units which can broadcast Wi-Fi signals as well. This is especially a promising approach for areas with lower positioning accuracy. Furthermore, with regard to the distribution of the waypoints along the pre-defined trajectories, it may be useful to expand the network. This is currently under way to achieve a finer grid for the radio maps.

With the latest generation of Wi-Fi hardware, the Round-Trip Time (RTT) between the APs and mobile devices can also be measured (see e.g. Van Diggelen et al., 2018; Guo et al., 2019; Horn, 2020). Wi-Fi RTT is a promising method for the future at TU Wien which would improve the achievable positioning accuracies. However, new hardware for the AP would be necessary and Android version 9 or higher on the smartphones. An implementation for the hardware of the APs can be done with the previously mentioned Raspberry Pi computers. However, RSSI fingerprinting will continue to have its legitimacy in view of non-existent, campus-wide coverage with new hardware which would not be economically justifiable. A combination with Wi-Fi RTT will therefore be effective. New algorithms are needed for such an integration and will be developed.

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BIOGRAPHICAL NOTES

Alexander Leb is a former master student at the Department of Geodesy and Geoinformation at TU Wien, Vienna, Austria. He received his BSc and Masters in Geodesy and Geoinformation in 2018 and 2020, respectively, dealing with indoor positioning using Wi-Fi.

Guenther Retscher is an Associate Professor at the Department of Geodesy and Geoinformation at TU Wien, Vienna, Austria. He received his Venia Docendi in the field of Applied Geodesy from the same university in 2009 and his Ph.D. in 1995. His main research and teaching interests are in the fields of engineering geodesy, satellite positioning and navigation, indoor and pedestrian positioning as well as application of multi-sensor systems in geodesy and navigation.

CONTACTS

Dr. Guenther Retscher
Department of Geodesy and Geoinformation
Research Division Engineering Geodesy
TU Wien
Wiedner Hauptstrasse 8-10   E120-05
1040 Vienna, AUSTRIA
Tel. +43 1 58801 12847
Fax +43 1 58801 12894
Email: guenther.retscher@tuwien.ac.at
Web site: http://www.geo.tuwien.ac.at/