Influence of the RSSI Scan Duration of Smartphones in Kinematic Wi-Fi Fingerprinting

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Key words: Wi-Fi positioning, kinematic system training, continuous training, RSSI scan duration dependence, workload reduction

SUMMARY

Nowadays Wi-Fi fingerprinting is a popular method for indoor positioning with smartphones. It is based on static RSSI (Received Signal Strength Indicator) measurements of the surrounding Access Points (APs) at reference points with known coordinates in the training phase. In this work, static training measurements are completely not foreseen as they are very time consuming and thus labour intensive. In contrast, waypoints are defined along the users' trajectories and the training phase is carried out kinematically while walking along and passing by. Kinematic measurements, however, pose much greater challenges than the usual static or stop-and-go measurements. In the experiments the Wi-Fi RSSI were measured with three different smartphones kinematically along two trajectories that started in front of the entrances of an office building leading through the ground floor and ending in the courtyard of the building. It could be shown that the results can vary significantly depending on the smartphone used, which is mainly caused by the duration of a Wi-Fi RSSI scan. This scan duration depends of course on the number of visible APs which was very different for the individual smartphones. The results of the position determination showed deviations from the ground truth of about 2 to 5 m, which is only slightly worse than with static training measurements. The big advantage is that no static training measurements but continuous system training is performed.

KURZFASSUNG

WLAN Fingerprinting ist heutzutage ein populäres Verfahren für die Indoor-Positionierung mit Smartphones. Dieses Verfahren basiert auf der statischen Messung von Signalstärken, den RSSI (Received Signal Strength Indicator), der umliegenden Access Points (APs) an den koordinativ bekannten Referenzpunkten in der Trainingsphase. In dieser Arbeit werden keine statischen Trainingsmessungen vorgenommen, da sie sehr zeitaufwendig und arbeitsintensiv sind. Im Gegensatz dazu werden Wegpunkte entlang der Trajektorien des Nutzers definiert, an denen die Trainingsmessungen kinematisch beim Vorbeigehen ausgeführt werden. Kinematische Messungen stellen jedoch eine wesentlich größere Herausforderung dar als die üblichen statischen bzw. Messungen im Stop-and-Go Modus. In den Experimenten wurden die WLAN-Signalstärken mit drei unterschiedlichen Smartphones kinematisch entlang von zwei Trajektorien, die vor den Eingängen eines Bürogebäude starten und durch das Erdgeschoß führen und im Hof des Gebäudes enden, gemessen. Es konnte gezeigt werden, dass je nach

verwendetem Smartphone die Ergebnisse stark variieren können, was im wesentlichen auf die Dauer eines WLAN-Scans zurückzuführen ist. Diese Dauer hängt natürlich von der Anzahl der sichtbaren APs ab und war sehr unterschiedlich für die einzelnen Smartphones. Die Ergebnisse der Positionsbestimmung ergaben Abweichungen von der wahren Position von rund 2 bis 5 m, was nur geringfügig schlechter als bei statischen Trainingsmessungen ist. Der große Vorteil ist dabei, dass kein statisches Training erforderlich ist und kontinuierliches Systemtraining ausgeführt wird.

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1. INTRODUCTION

For numerous smartphone applications, such as Location Based Services (LBS), it is important to know the current location of the user. Indoor applications are found, for example, in shopping malls, hospitals, airports, office buildings and factories. As there is wireless Internet in almost every public building today, measuring Wireless Fidelity (Wi-Fi) signals is the most popular method to determine the position of a smartphone user (see e.g. Liu et al., 2007; Vanson Bourne, 2016). There are several approaches for using the measured Received Signal strength Indicator (RSSI). In this work Wi-Fi location fingerprinting is the selected technology. For fingerprinting two different phases have to be distinguished, i.e., the off-line training phase to establish a database of RSSI values in the area of interest and the on-line positioning phase where the current RSSI measurements are used to obtain the users' location (Fang et al., 2008; Khalajmehrabadi, 2016). In this study, the static training phase which requires measurements on a high number of reference points in the area of interest creating high workloads is omitted, but system training is performed from kinematic measurements along the trajectories from the start point to the users' destination.

The paper is organized as follows: In section 2 the creation of the fingerprinting radio map with three different interpolation techniques is analyzed and the most suitable one selected. Section 3 describes the characteristics of the test area and smartphone specifications used in the experiments. The conducted analyses and major results are presented in section 4 followed by a discussion of the results in section 5. Finally, conclusions are drawn in section 6.

2. CREATION OF A FINPRINTING RADIO MAP

The RSSI values in the fingerprinting database are used to calculate the so-called radio map using interpolation approaches. It is a map that maps the RSSI of a Wi-Fi Access Point (AP) in a specific area. For the interpolation the natural neighbour interpolation is most commonly used (see e.g. Ledoux, and Gold, 2005) whereby Voronoï diagrams and Delaunay Triangulations are applied (Fortune, 2004; Lee and Han, 2012). The propagation of Wi-Fi signals, however, is influenced by different effects, such as short- and long-time signal variations and fluctuations, which cause problems when creating a radio map. Since indoor environments contain many different physical objects, it is very difficult to model these effects accurately. Nevertheless, there are some propagation models that take these effects into account, such as the empirical one-slope model, which is based on the principle of free space attenuation, and the semi-empirical multi-wall model, which takes into account the attenuation properties of existing walls between an AP and the user. Furthermore, there are Ray Launching and Ray Tracing, which are deterministic propagation models in which the effects of physical propagation, i.e., absorption, refraction and reflection, are modelled using objects (Katircioğlu et al., 2011; Retscher and Tatschl, 2017). Thereby the basis for the model is a digital plan of the measuring area, in which all walls and coordinates of the APs are contained (Roos et al., 2002; Wang et al., 2011). The advantage of such a radio map creation is that no RSSI measurements would be needed and the map can be changed more easily if something changes in the Wi-Fi infrastructure (Cavalieri, 2007). The main disadvantage of such a radio map creation, however, is that the map is not based on the measured RSSI in the environment and thus cannot reflect the RSSI distribution in detail. Hence, RSSI measurements are usually performed in the fingerprinting training phase. The radio map depicted in Figure 1 is based on an empirical model of measured RSSI from a kinematic survey. In general, the size of the data set of a radio map depends on the grid size and the number of APs whereby the key elements are the number and distribution of the known reference points on which the RSSI measurements are carried out in the training phase. Between the reference points the RSSI values and distribution need to be interpolated which is decisive for the later accuracy of positioning. The closer the grid reference points are, the higher the resolution of the radio map. For the radio map in Figure 1 the raster width was selected at one decimeter. Three different interpolation methods were investigated, i.e., linear interpolation, natural neighbour interpolation (the aforementioned Voronoï interpolation) and spline interpolation.

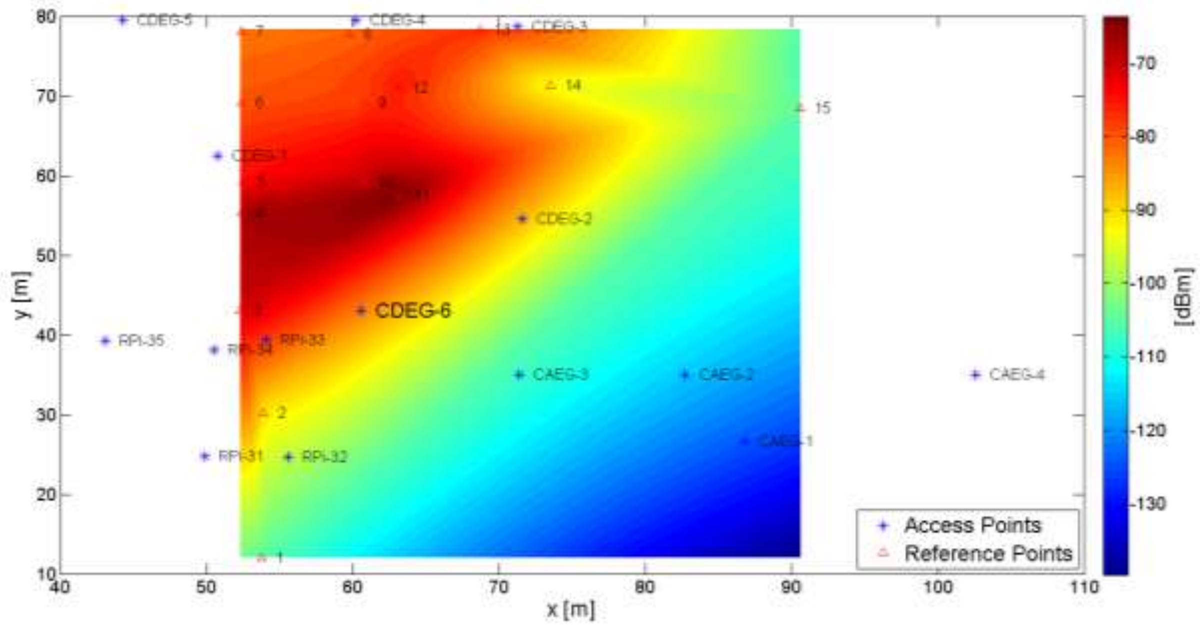

Figure 1. Radio map of AP CDEG-6

Table 1 lists the achievable mean deviations from the ground truth for positioning with the three different interpolation methods for the two different trajectories described in section 3. For that purpose, averaged radio maps are derived from the whole dataset of the kinematic measurements on the reference points along the trajectories using these three approaches. Since only the time and not precisely the RSSI were recorded during the kinematic measurements at the reference points, a method had to be found to obtain the RSSI values at the reference point time. The RSSI value of the closest time stamp at the reference point time was used as the reference point value (referred to as 'closest' in Table 1) for the first approach, and in the second approach the RSSI values between the time stamps were interpolated linearly and the value with the same reference point time was taken (referred to as 'linear' in Table 1). If RSSI with a value of lower than -105 dBm were obtained during interpolation, this number was set. As can be seen from the Table, the 'linear' method delivers smaller deviations than the 'closest' method for trajectory 1. It can also be seen that Voronoï and linear interpolation deliver better results than spline interpolation. In trajectory 2, on the other hand, the 'closest' method delivers slightly smaller deviations. As the differences between the interpolation methods are marginal it is concluded that there is no universally valid interpolation method for creating a radio map. In order to have a uniform method, the 'linear' method was used together with the Voronoï interpolation for further calculations.

Interpolation method	Trajectory 1	Trajectory 2
Linear, closest	4.70	4.30
Voronoi, closest	4.56	4.25
Spline, closest	5.33	**4.14**
Linear, linear	4.40	4.59
Voronoi, linear	**4.17**	4.57
Spline, linear	4.44	4.75

Table 1: Mean deviations in [m] of the different radio map creations

3. TEST AREA CHARACTERISTICS AND SMARTPHONE SPECIFICATIONS

Experiments were conducted in an University office environment where Wi-Fi infrastructure was available. The infrastructure consisted of Cisco Wi-Fi routers of model AIR-CAP2602E-E-K9 and AIR-CAP2702E-E-K9. In addition, five Raspberry PI units configured as APs were used to cover the entrance area of the building ensuring full Wi-Fi reception. In this paper results of the experiments on the ground floor are presented. Figure 2 shows the area indicating two selected trajectories. The first trajectory 'EI7_Run' is 150.6 m long and leads over 15 waypoints from reference point RP1 through the main entrance into the hallway and auditorium VII to its end point RP14 at the exit to the inner courtyard of the building. The second 79.7 m long trajectory 'EG_CR' has also 15 waypoints and starts at the side entrance of the building and then continues to an anteroom in front of the class room and leads then through an area with permanet desktop computers into the courtyard. Both trajectories were measured with normal walking speed several times in both directions, with an average duration of a tets run of 120 seconds for trajectory 1 and 64 seconds for trajectory 2, respectively, In order to get enough comparison values of the Wi-Fi signals and to take into account the temporal and environment-dependent signal variations, measurements were carried out on different days and times of the day. Three different smartphones were used (see Table 2) where all of them used the IEEE 802.11a/b/g/n standard. Additionally, the Sony Xperia Z3 uses the newest standard IEEE 802.11a/b/g/n/ac. An inhouse developed smartphone App developed by Hofer was used for data recording (Hofer and Retscher, 2017). Since the smartphones contain different Wi-Fi chips, they result in different scan durations. Table 2 shows also the average scan durations and it can be seen that two smartphones have a quite long duration of around 4 seconds while the third of only 1.2 seconds. The scan duration has a major influence on the number of scans recorded for each run which results in different positioning accuracies (see section 4.2).

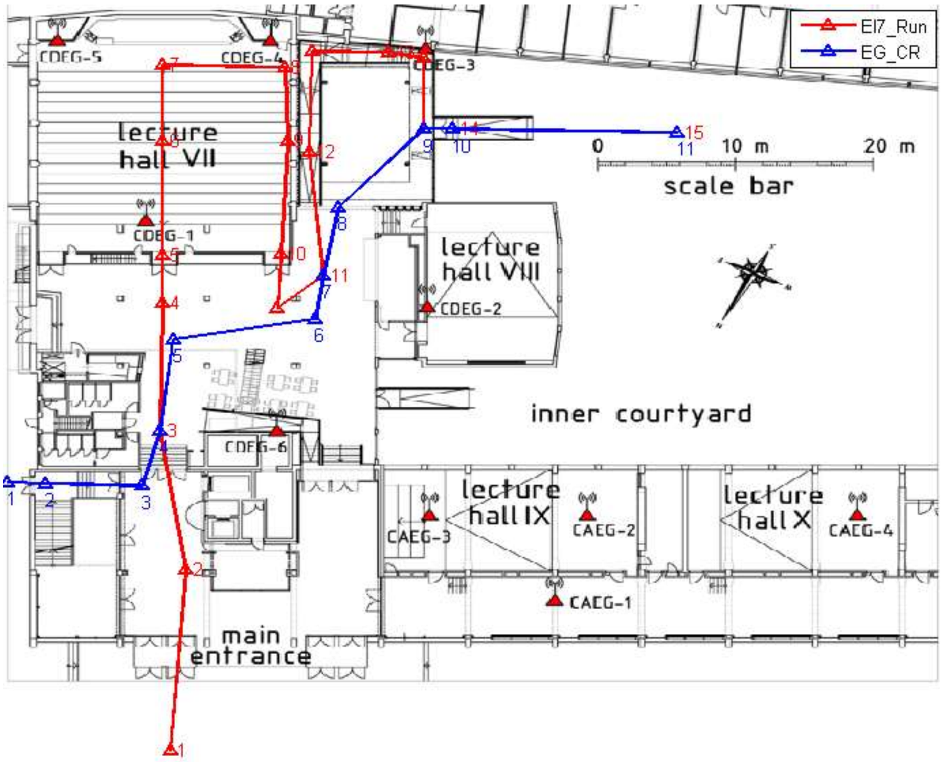

Figure 2. Map of the test area indicating the two trajectories

Name	**Samsung Galaxy S3**	**Samsung Galaxy A3**	**Sony Xperia Z3**
Model	GT-I9300	SM-A310F	D6603
Abbreviation	S3	A3	Z3
Wi-Fi	802.11a/b/g/n	802.11a/b/g/n	802.11a/b/g/n/ac
Frequency band	2.4 GHz, 5 GHz	2.4 GHz	2.4 GHz, 5 GHz
Sensors	accelerometer, gyroscope, air pressure sensor, compass	accelerometer, gyroscope, compass	accelerometer, gyroscope, air pressure sensor, compass
Wi-Fi scan duration in [s]	3.6	1.2	4.2

Table 2: Smartphone specifications

4. MAIN RESULTS OF THE EXPERIMENTS

Several investigations using the kinematic RSSI scans obtained along the two trajectories shown in Figure 2 are presented in this section. For the calculation of the positioning results, the deterministic Nearest Neighbour (NN) and k-Nearest Neighbour (kNN) algorithm were employed. The different test runs and smartphones are compared and it is examined how a change in the number of APs affects the results.

4.1 Comparison of Different Test Runs

Table 3 compares the individual test runs and reference points for trajectory 1 whereby the colours of the columns corresponds to the three different smartphones, i.e., yellow for the Samsung Galaxy S3, orange for the Samsung Galaxy A3 and blue for the Sony Xperia Z3. The numbers in green indicate that the respective reference point was determined with no deviation from the ground truth. One can see that reference point RP2 could be determined 10-times from all 20 test runs without any deviation. The overall best run was No. 11 with an average deviation of around 2.2 m where the Samsung Galaxy S3 was used. The runs with the largest mean deviation of around 6.8 m were runs 16 and 20 using the Sony Xperia Z3. Table 4 shows the results from the second trajectory. Along this trajectory reference point RP8 showed no deviation 7-times. Moreover, it can be seen that run 14 with the Samsung Galaxy A3 resulted in the smallest mean deviations. Again the largest mean deviation of 9.8 m were obtained with the Sony Xperia Z3 in run 11.

4.2 Scan Duration

Table 5 compares the scan duration and resulting number of scans for the test runs along the two trajectories. The individual smartphones are colour-coded as above. It is particularly noticeable that the number of scans is much higher for the test runs carried out with the Samsung Galaxy A3. This is obviously due to the different scanning intervals of the smartphones listed in Table 2. As seen above, this smartphone performed best which proves that the scan duration has major impact on the achievable positioning results.

4.3 Smartphone Differences

Table 6 compares the positioning results of the three smartphones whereby no device specific radio map but the one with the averaged values of all training measurements was used for the calculations. Furthermore, the interpolated time was used here as reference time. As can be seen from the Table, the Samsung Galaxy S3 delivers the best result for trajectory 1 with an average deviation of 3.30 m. However, the same smartphone results also in the largest mean deviation of 6.08 m in trajectory 2. Samsung Galaxy A3 delivers good results in both trajectories with a deviation of 3.71 m and 2.96 m respectively. The Sony Xperia Z3 was the worst performer, with an average deviation over 5 m for both trajectories.

	Run									
Deviation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RP2	0.00	0.00	0.00	6.23	3.90	2.41	0.00	0.00	0.00	2.21
RP3	3.32	3.20	10.00	4.19	5.80	6.89	2.31	2.40	10.38	7.32
RP4	1.70	9.18	1.80	2.90	5.50	4.48	1.39	3.70	0.30	5.40
RP5	1.30	7.58	0.40	9.60	3.30	9.30	7.49	3.80	12.43	4.90
RP6	10.27	6.30	0.20	0.40	0.00	2.20	12.37	3.93	0.71	0.51
RP7	8.20	1.60	9.00	7.41	6.50	9.50	6.00	2.90	9.63	1.00
RP8	0.00	0.00	6.11	7.52	2.75	1.20	4.30	0.00	3.06	0.00
RP9	1.51	10.02	0.14	2.38	4.18	2.56	0.00	8.79	0.00	0.94
RP10	1.36	7.11	4.77	3.89	9.68	2.60	3.80	8.42	9.61	3.00
RP11	0.50	3.81	2.62	6.86	1.70	1.81	1.36	3.78	2.53	3.11
RP12	1.14	0.78	1.30	8.60	0.61	0.00	6.16	0.85	1.00	7.29
RP13	1.40	8.60	0.90	0.00	0.00	0.00	1.00	1.75	1.88	1.60
RP14	7.89	6.33	6.26	12.20	2.15	5.55	7.84	9.95	11.80	9.65
mean	**2.97**	**4.96**	**3.35**	**5.55**	**3.54**	**3.73**	**4.16**	**3.87**	**4.87**	**3.61**

	Run									
Deviation	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
RP2	0.00	0.00	0.00	5.62	3.52	2.35	0.00	1.60	4.41	3.20
RP3	0.80	4.87	4.50	1.43	10.07	5.30	0.76	0.30	15.70	4.62
RP4	5.47	10.25	2.24	1.60	6.10	3.31	3.04	1.90	6.12	10.90
RP5	2.50	12.84	0.00	3.90	5.91	5.97	1.40	3.20	4.30	5.90
RP6	2.90	0.00	5.72	1.80	2.40	9.43	2.10	1.10	9.34	2.12
RP7	2.11	2.00	3.61	3.50	0.20	9.09	6.11	3.80	10.20	10.70
RP8	1.90	4.10	0.00	7.74	2.62	8.42	4.02	7.50	3.14	12.38
RP9	3.13	8.76	0.00	3.08	5.42	5.30	1.66	3.36	0.00	9.58
RP10	5.32	1.25	1.89	3.24	5.97	6.24	11.19	4.18	8.42	4.59
RP11	0.14	0.14	3.36	4.49	1.70	13.69	3.14	3.00	0.58	5.98
RP12	0.00	0.00	3.57	1.08	0.00	7.25	1.66	0.92	0.30	7.25
RP13	0.20	0.00	3.18	3.01	1.70	0.10	2.79	3.10	1.60	1.50
RP14	3.97	4.47	10.93	8.74	9.03	11.28	8.54	9.40	7.36	9.11
mean	**2.19**	**3.75**	**3.00**	**3.79**	**4.20**	**6.75**	**3.57**	**3.34**	**5.50**	**6.76**

Table 3. Comparison of all test runs along trajectory 1 (deviations in [m])

	Run									
Deviation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RP2	0.20	1.81	2.01	3.11	2.81	1.32	0.22	2.31	2.61	3.81
RP3	5.92	1.97	6.42	1.77	16.17	0.50	5.42	1.94	6.22	6.64
RP4	0.22	3.90	5.34	0.71	3.42	0.42	4.34	5.47	4.24	8.80
RP5	5.73	0.40	7.51	7.62	2.21	5.40	7.38	0.42	7.31	3.67
RP6	1.63	5.66	4.77	7.65	1.33	1.84	1.22	2.75	5.23	3.85
RP7	0.95	1.36	1.90	4.19	0.20	2.38	0.36	2.69	3.11	3.74
RP8	0.32	0.10	6.51	0.00	2.15	0.00	0.67	0.00	6.32	0.00
RP9	1.20	3.53	1.70	3.80	9.28	3.14	2.00	1.20	1.80	6.70
RP10	13.38	6.20	3.41	8.50	2.97	6.20	8.56	7.50	4.30	8.40
mean	**3.28**	**2.77**	**4.40**	**4.15**	**4.50**	**2.36**	**3.35**	**2.70**	**4.57**	**5.07**

	Run									
Deviation	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
RP2	40.93	38.51	0.63	2.41	3.41	4.40	0.20	3.21	5.00	5.75
RP3	31.72	5.06	9.71	1.36	6.42	3.42	5.62	4.52	6.72	3.83
RP4	0.71	8.09	2.91	2.91	8.78	8.68	6.67	2.69	17.64	4.47
RP5	9.31	5.64	6.80	0.20	3.11	1.84	1.24	1.35	2.52	12.70
RP6	1.73	2.84	2.55	4.39	6.55	6.63	0.00	4.34	4.90	11.37
RP7	0.00	2.09	1.14	0.22	1.60	4.78	0.14	0.10	4.02	7.96
RP8	0.00	0.00	0.32	0.00	0.82	8.56	1.41	0.63	4.54	5.98
RP9	2.00	1.00	1.80	1.80	1.40	13.40	1.30	4.16	8.26	10.20
RP10	2.21	5.30	6.48	7.80	4.10	10.10	5.56	7.60	4.30	8.40
mean	**9.84**	**7.61**	**3.59**	**2.34**	**4.02**	**6.87**	**2.46**	**3.18**	**6.43**	**7.85**

Table 4. Comparison of all test runs along trajectory 2 (deviations in [m])

4.4 Dependence on AP Number

In order to investigate the effects of the number of APs which are used for the calculations on the achievable accuracies, a further analysis of the RSSI values was conducted. As the network consists of multiple SSIDs (Service Set Identifiers), one physical AP can have three MAC adresses. In the first case of investigation all three MAC addresses were used individually and in the second case the averages of the RSSI values of the three MAC addresses were used for the calculations. Thus, the number of used MAC addresses corresponds to 35 and 15, respectively. Since the APs CAEG-1 to 4 are quite far away from the trajectories (compare Figure 2) and there are almost no high RSSI values received from them, they were omitted in a further third calculation (11 APs) As shown in Table 7, the more APs are used, the better the result for both trajectories. If only 15 or 11 APs are used instead of 35 the mean deviations increase to around 4.6 from 4.2 m for trajectory 1 and to 4.9 from 4.6 m for trajectory 2.

	Trajectory 1		Trajectory 2	
Run	Duration [s]	Scan No.	Duration [s]	Scan No.
1	133	115	68	59
2	124	108	67	58
3	127	35	65	15
4	124	29	62	15
5	123	32	69	20
6	115	33	64	19
7	139	118	64	55
8	124	106	60	51
9	130	30	65	15
10	135	32	60	14
11	119	34	59	17
12	112	32	60	17
13	114	98	72	62
14	116	100	65	56
15	117	27	68	16
16	114	27	66	18
17	118	100	64	55
18	116	100	63	55
19	119	27	64	14
20	112	27	62	15

Table 5: Scan duration and number for the test runs

Smartphone	Trajectory 1	Trajectory 2
Samsung Galaxy S3	3.30	6.08
Samsung Galaxy A3	3.71	2.96
Sony Xperia Z3	5.07	5.42

Table 6: Mean deviations in [m] of the different smartphones

No. APs	Trajectory 1	Trajectory 2
35	4.17	4.57
15	4.60	4.87
11	4.62	4.85

Table 7: Mean deviations in [m] in dependence of used APs

4.5 Resulting Trajectories

Finally, the two trajectories were investigated as a whole, i.e., including the RSSI scans for a total run. The shown trajectories in Figures 3 and 4 were smoothed with a moving average filter. On the left the best resulting trajectory and on the right the worst result is shown. As previously seen, run 11 shows the best result with an average deviation of around 2.2 m for trajectory 1 and run 14 with a deviation of 2.3 m for trajectory 2. The worst results with a deviation of around 6.8 m delivers run 20 for trajectory 1 and run 11 with 9.8 m for trajectory 2. If one looks at Figure 4 on the right it is notable that the trajectory starts with a totally wrong starting position, which lies about 55 m away from the true position. On the other hand, the result of run 14 measured with the Samsung Galaxy A3 follows the ground truth very precisely (Figure 4 left).

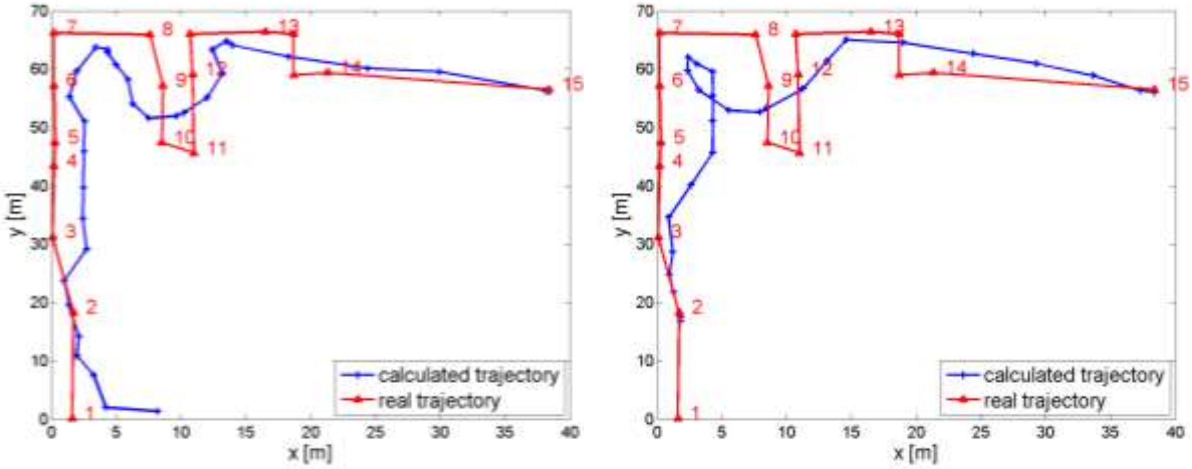

Figure 3. Results of two test runs along trajectory 1

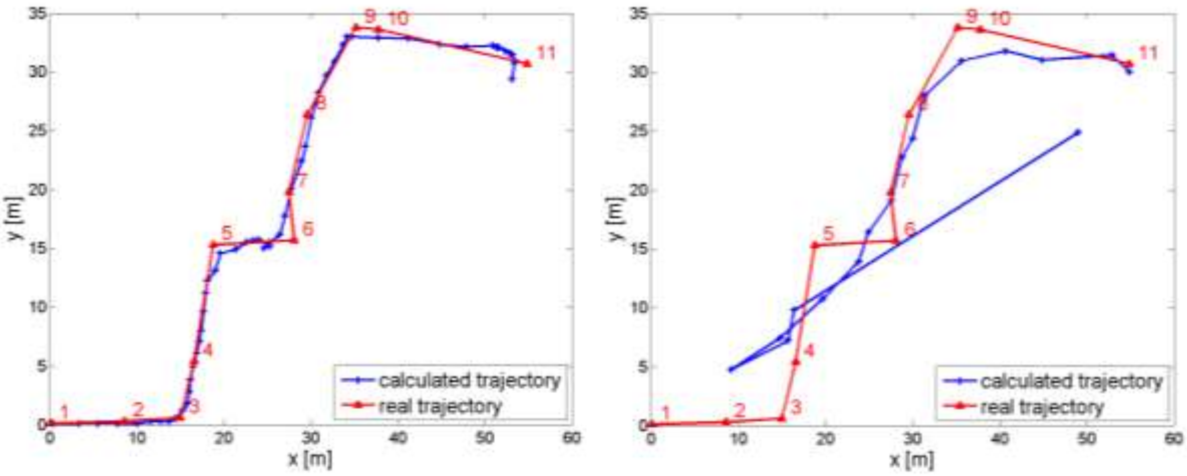

Figure 4. Results of two test runs along trajectory 2

5. DISCUSSION OF THE TEST RESULTS

Kinematic system training is very challenging but it could be shown that it can deliver only slightly worse results as usually obtained in Wi-Fi location fingerprinting with static training measurements leading to high workloads. As expected, the test results reveal that significant differences can be seen depending on the employed smartphone. Due to the different location and type of antenna in the smartphones, the same measured RSSI value does not necessarily result at the same position (Grossmann et al, 2007). This hardware dependence has a negative influence on the accuracy of the position determination. Device-dependent fingerprints can be derived from RSSI measurements by normalization; e.g. the relative relationship between pairs of APs can be used instead of the absolute RSSI measurement (Retscher et al., 2018). Furthermore, the differences between the RSSI values can also be used to obtain device-dependent fingerprints (Khalajmehrabadi, 2016).

The NN method was used to calculate the positions of the smartphone user. First the Euclidean vector distance for each fingerprint in the radio map was determined individually and then the minimum value was searched in the radio map. Then the deviations from the true coordinates were calculated for each reference point. Large deviations are mainly caused by (compare Khalajmehrabadi, 2016):

1. Multipath effects which occur due to short-term obstacles, e.g., furniture, people, etc.;
2. AP availability: some APs may be temporarily unavailable or unstable due to disturbances, energy loss, etc.;
3. Signal strength changes: APs can change the RSSI when the number of clients changes;
4. Different number of APs: there is no guarantee that an AP is always available during the training and positioning phase.

The last influence can be prevented with continuous system training as it was done in this study. Thus, its influence is reduced to a minimum as both phases took place simultaneously in this work.

If several positions with a small distance are found, a set of points with the k-smallest distances can also be selected (i.e., kNN method). Therefore, it was investigated whether the kNN method achieves better results than NN. The center of gravity of the k-nearest points with k from 1 up to 15 was calculated and the deviations obtained. The results showed that there was no significant improvement of the mean deviations in either trajectory. Contrary to the expectations, the mean deviations even increased slightly as the value of k increases. However, this increase was only in the centimeter range.

6. CONCLUSIONS

The aim of this study was to carry out indoor positioning based on Wi-Fi fingerprinting without static training phase measurements. The main advantage of Wi-Fi compared to other techniques, such as Bluetooth iBeacons or RFID, is that many public buildings already have the necessary infrastructure. Besides fingerprinting, there are other methods for indoor positioning. These are mainly trilateration and cell-based solutions. The later, however, has a poor accuracy depending on cell-size and is therefore only used as an approximate solution.

During the analysis, the fingerprinting radio map was created in different ways and with different reference data sets. It was seen that there is no generally valid interpolation method for radio map creation. Depending on the trajectory, the Voronoï or spline interpolation showed the smallest deviations. It can be assumed that the observed positioning errors could have been reduced by an improved reference data collection. This mainly concerns the distance between the reference points. At a smaller distance with more reference points more RSSI values for the radio map creation would be available. The determination of the signal strengths at the refereece points also did not yield a clear result. The reference data set, in which the RSSI values are averaged at the reference points and which contains the highest number of visible APs, turns out to be the best. Contrary to the expectations, there is no improvement in the application of the kNN method as opposed to the simple NN method.

Kinematic measurements pose a much greater challenge than static measurements or in stop-and-go mode. How long a Wi-Fi scan takes depends on the number of visible APs and has a large influence on the results. In practice, kinematic RSSI scans were performed with three different smartphones. The smartphone with the longest scan duration delivered the worst results for both trajectories with an average deviation of more than 5 m. The reason for this is the long average scanning time of around 4.2 seconds. The other two smartphones delivered better results, i.e., averaged over the whole test runs, the mean deviation of all smartphones for trajectory 1 was 4.2 m and 4.6 m for trajectory 2, respectively.

In general it can be said that the achieved positioning accuracies for the kinematic system training are not much worse than with static measurements. The big adavantage, however, is that the training phase is much shorter and continuous system training can also be carried out. A further improvement of the positioning accuracies can be acheived by combined use of the inertial smartphone sensors, such as accelerometer, gyroscope and magnetometer, for dead reckoning navigation, as was shown in the paper of Retscher and Hofer (2017). This is subject of further investigations.

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BIOGRAPHICAL NOTES

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