Development of a WiFi-Fingerprinting for Position Determination by Mean of Probabilistic Methods

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SUMMARY

Caused by the rapid technical development in the recent 30 years the question relating to position specification and navigation of pedestrians in the outside location could nearly be solved. GNSS-systems are working on almost all transportable devices, e.g. smartphones or tablets - consequently they can be used at any time, at any location. But this solution is restricted to outdoor areas, within buildings the GNSS-systems are only of limited use. Due to this fact other approaches need to be found for the interior area. Here, positions can be determined by infrared-, ultrasonic- or radio-contacts, whereby in these cases investigations in infrastructure are often needed. Another alternative is the position determination by wireless-LAN-signals. Mobile LAN access points exist in considerable numbers in a lot of public buildings and therefore they are very attractive for real-time tracking. Based on this knowledge, the Hafen-City-University Hamburg (HCU) has worked in the context of the study project 'Location Based Services' (LBS) on the opportunity of a positioning with wireless-LAN by a Fingerprinting-method. In this connection all questions related to the implementation, achievable accuracy as well as the type of position determination are identified. Based on these questions, different forward thinking approaches and algorithms needed to be tested - on the one hand to generate a more precise position specification, on the other hand to enable a fast calculation of the position. In this scientific work the approach to the project, it's processing and the achieved results are described. The focus is on the development of a Fingerprinting-method, based on a probabilistic approach. This is the algorithm of the Occupancy-Grid Mapping which is used for detection with laser- and ultrasonic-sensors for robots and thus belongs to the SLAM-algorithm (Simultaneous Localization and Mapping). Based on this algorithm, accuracies of 0.3 - 3.0 meters could be achieved at the end of the project. These results show that the Occupancy-Grid-method is useful for a personal indoor localization.

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1. INDRODUCTION

The use of navigation systems became routine for many people. They are being used in various situations, whether on the way to work or on holiday. The use of GNSS-signals on smart-phones and tablets enables many users to solve their daily navigation needs. In addition, many applications offer location based services (LBS), which provide information based on the users current position. However this supply of information comes to a stop at the threshold into buildings. The gap between accurate positioning indoors and outdoors is still not sufficiently closed. Inside buildings GNSS-signals are shielded and positioning needs to be accomplished by other means. The HCU-Hamburg is therefore already for many years engaged in finding indoor positioning solutions. In order to use LBS indoors, the user's position has to be determined first. This can be accomplished by multiple technologies, such as ultrasound, infrared, Bluetooth or WiFi-Signals. These technologies differ in their accuracy, range and installation complexity. All technologies require communication between a transmitter and a receiver. In this point the WiFi-signals are set apart form to the other technologies, since nearly complete WiFi-coverage is already provided in many shops, restaurants, public institutions or business buildings. Based on this infrastructure, users can solve their navigation problems by using their smart-phones and the signals send by the WiFi access points. Hence, LBS can also be provided inside GNSS-signal shielded areas. This is especially useful in large buildings with confusing layouts, such as convention centers. This technology can offer routing to specific rooms, shops or exhibits. Entire security models can be based on this technology. This paper investigates indoor positioning based on WiFi-signal strength. The user's position is hereby determined by using fingerprints.

2. POSITIONING VIA WIFI

A Wireless Local Area Network (short WLAN) describes wireless communication between computers in a network (Linzner, 2010), however ideas and concepts exist to adapted this communication signals for positioning similar to ultrasound or infrared methods. The main argument for using WiFi-signals is the existing infrastructure, whereas the infrared and ultrasound components have to be installed first (Kemper, 2010). The WiFi-signal itself or the strength of the signal can be used. Generally the signal can be used in three different ways to determine a position.

- 1. Angle Of Arrival (AOA)
- 2. Time of Arrival (TOA)
- 3. Received Signal Strength (RSS)

(Zekavat et al. 2011)

These various methods to determine a position using WiFi-signals allow an miscellaneous technical application. However, the specific WiFi-characteristics have to be accounted for. The signals can cover up to 50-100 m in the open field (Linzner, 2010). Therefor the positioning is only available in a very close range. Additionally, WiFi-signals work in the microwave frequency ranges of 2.4 GHz and 5 GHz, in which different characteristics can occur. These differences can affect the positioning (Oschatz, 2011). The 2.4 GHz frequency is mostly used by older WiFi-products (Linnhoff-Popien et al., 2010). The wide availability of 2.4 GHz frequency seems to be appealing for the majority of mobile devices. Additionally, the human body has a mayor influence to the spreading of WiFi-signals. The human body consists to 75 % out of water, therefore the absorption of wireless signals is considerable and can lead to a measurable signal strength deviation.

2.1 Angle- and Time of Arrival Methods

Angle based methods determine the position by finding the angel of the received signal either at the access point or at the mobile user device. The angle between two access points, as well as their position allows the calculation of the user's position. The calculation is exclusively done by triangulation methods. In the area of WiFi-positioning this method is theoretically tested using the approach of multiple access points to determine the angle. Investigations by Peng and Sichitiu (2006) show that high accuracy can be already are achieved with a small number of access points and poor angle accuracy.

The Time of Arrival (TOA) positioning method on the other hand is based on the distance between the transmitter (tx) and receiver (rx). Different methods are known to calculate the distance, which are well covered in literature (Zekavat et al., 2011). Basically propagation time and speed of the transmitted wave are considered. In the easiest case the distance can be calculated by the simple distance between transmitter and receiver. In this case the calculation is performed at the receiver end (see Figure 1). It is assumed that both devices work in the same time frame. If this can't be assured the distance is duplicated (tx - rx - tx). The position can be determined by application of the sphere equation (Blankenbach et al., 2007):

$$s_i^2 = (x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2$$

For all time based measurements applies: the higher the time resolution, the better the distance measurement. Unfortunately the standard clocks build into WiFi-devices provide a poor time resolution. Due to a signal speed close to light speed (299792 m/ms) a massive error in the distance can occur even with small deviations in time.

The Eberhard Karls University Tübingen created a working positioning system using time based measurements called Goodtry. They use time marks inside the data packages for calculating the signal propagation time. Goodtry uses existing access points and mobile devices. Therefore the signals propagation time measurement is determent by the clock's resolution. For instance an error of one nano second results in an error of ~300 meter (Hoene, 2014).

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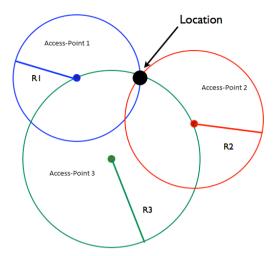


Figure 1: Trilateration of one point (TOA)

2.2 Signal Strength Methods

In difference to the first two methods the Received Signal Strengths (RSS) method measures the remaining signal strength from the transmitter at the receiver. Basically two different approaches can be named: the RSS and the recognition of patterns (Fingerprinting). Fingerprinting attempts to determine the position by comparison to a given matrix. Depending on the method and surroundings the accuracy can vary.

2.2.1 <u>Received Signal Strengths</u>

To use the signal strength for positioning, the transmitted and received strength have to be readout. These are stated in watt or dBm (Decibel-milliwatts). The ratio between received and transmitted strength is stated as free space loss or signal absorption. The ratio in dB is given by:

$$SV_{dB} = 10 * \log(\frac{S}{E})$$

In this formula S describes the transmitted and E the received signal strength, both given in watt. The signal absorption SV_{dB} is directly connected to the distance between the transmitter and receiver and is given by the following formula:

$$SV_{dB} = 32.45 + 20 * \log(r) + 20 * \log(f) - 10 * \log(GE)$$

, where the distance r is given in km, the frequency f in MHz and GE is the signal gain due to the isotropic radiator (Menz, 2005). The calculated distances can be used for the trilateration of the position. Unfortunately this can only be used in a free space without resistance. As explained humans, objects or walls interfere with the signal. This absorption worsens the

correspondence between signal strength and distance, which will lead to wrong positions if no additional information is used. Physical models are necessary for correction, which are very complex. Therefore their parameters are sensitive to small changes and often lead to unwanted results. Ferris et al. (2006) use adjusted models in combination with signal strength for tracing a person's movement indoors.

2.2.2 Fingerprinting

The principle of location fingerprinting is based on the collection of signals, whose strength is weakened by distance to the transmitter. It follows that the received signal strength of all access points is unique at every point in a room, like a fingerprint is unique and can be recognized again later. The positioning using a signal fingerprint works in two different phases. In the first phase (offline phase) the signal strengths are recorded and saved in a radiomap. The positions of the measurements are defined in a grid inside the building (Zekavat et al., 2011). This radio-map database is composed of the RSS of the access points within range and the coordinates of the corresponding position. Due to the above-mentioned characteristics of WiFi-signals, the measurements should be repeatedly performed facing different directions. Hereby the signal shielding due to the human bodies can be excluded. In the second phase (online location phase) a RSS measurement is taken at an unknown position and compared to each point in the radio-map. The position is given by the point in the radio-map with the greatest correlation to the measurement.

Different methods are known to create the radio-map in the offline phase. For example empirical data can be collected. This is relatively time consuming and whenever a part of the network changes the measurements have to be repeated in the affected area. Another method is the creation of a mathematically modelled radio-map. Unfortunately this mathematical model is very complex due to multiple variables like, position of transmitters, wave distribution, signal strength, reflection and diffusion (Linnhoff-Popien et al., 2010). Another factor for the quality of the radio-map is the grid resolution. However a smaller grid resolution does not necessarily mean a better radio-map. Zuendt et al. (2014) could proof that a grid width of two m is sufficient for accurate positioning via fingerprinting. In Figure 2 the RSS grid is shown with a cubic interpolation. The figure's left part shows 177 grid points used to create the radio-map. The right part of the figure shows the same layout with only 18 grid points. Even though the left side has a better resolution, no relevant information for positioning is lost by using lesser grid points (Zuendt et al., 2004).

The different algorithms used for positioning can be divided into probabilistic and deterministic methods. Deterministic methods describe the propagation of electromagnetic waves in a certain area. These models consider multiple influences such as reflection and diffusion. The information needed for these models are gathered in the offline phase by measurements. During the online phase the current (one-shot location) is obtained by using the radio-map. It is not possible to state the quality or reliability of the positions. These parameters can be determined by using a probabilistic method. The aim of probabilistic methods is to create a probability for each position in the grid. The positioning algorithm runs within an iterative loop and weights each possibly position by its correlation. Therefor this method can deliver a distinct proposition of the position and its quality and reliability.

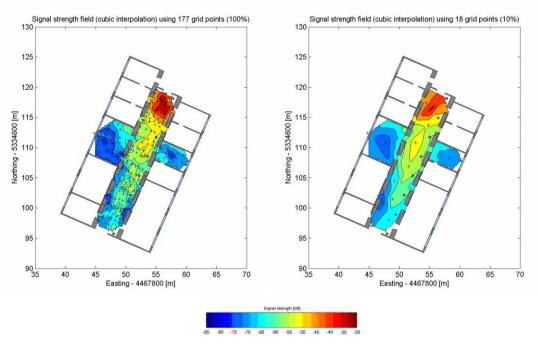


Figure 2: Radio-map with different resolution (Zuendt et al., 2004)

3. REALIZATION OF A FINGERPRINTING

In the previous chapters different approaches for WiFi positioning are shown. In this project a fingerprinting approach is realized at the HCU. The methods and procedures are explained in the following.

In the first quarter of 2014 the new HafenCity university building was opened. For uninterrupted internet access 150 access points have been installed all over the university. Aironet 1600i devices supplied by the company Cisco were chosen. This model supplies the three standards IEEE 802.11 a/g/n. The 802.11a and 802.11n standards transmit data in the 2.4 GHz frequency range. 802.11g and 802.11n standards support the 5 GHz frequency range. Even though the devices offer both frequency ranges only the 2.4 GHz frequency range is used up to now at the HCU. Therefor no comparison between the two ranges in regards to their potential for positioning is possible. Due to the size of 180.000 m² area at the HCU, this research is limited to the public area in the fourth floor.

The fourth floor offers free spaces as well as narrow floors. Therefor varying surroundings can be examined using the new WiFi-positioning method. The definition of the grid inside the fourth floor is described, which is used as the basis for further testing.

As stated by Zuendt et al. (2014) a grid width of 2 m is sufficient for the positioning via fingerprinting. Hence, a 2 x 2 m grid is inserted into the public spaces of the fourth floor. The metric and UTM global referenced plant layout is used (see Figure 3). This allows referring to the locations in UTM coordinates.

These digital grid points are transformed into locations by the use of a total station. The measurement of the RSS is performed by a smart phone with the Android application HCU-Sensor-App. The correct order of the points is vital for the correct connection to the points in the radio-map database. The RSS is collected from all access points within range for 30

seconds at each grid point. The collected data by the HCU-Sensor-App contains the MACaddress, the RSS and the frequency as well as the phone's time at the measurement. The timestamp allows the connection of the grid point to the corresponding point in the radio-map. In Figure 3 the floor plan is shown with 250 grid points. Table 1 shows part of the database. In the first column contains the point ID, the next two columns describe the coordinates. Thereafter, each pair of two columns describes the RSS in dB from the access point with the given MAC-address.

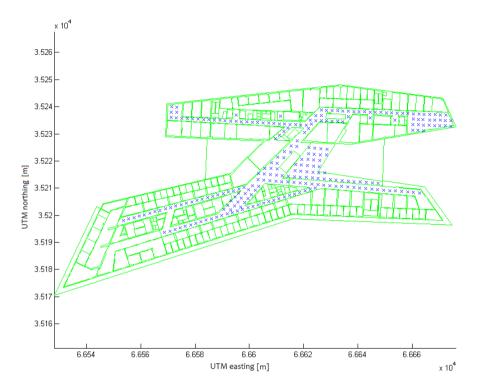


Figure 3: Floor plan with 250 grid points of fourth floor at HCU

Point	Easting [m]	Northing [m]	Mac1 [string]	RSS1 [dB]	Mac2 [string]	RSS2 [dB]
1	6667.37	35234.85	'00:1c:b3:af:39:cb'	-80.8	'0c:27:24:e0:fe:61'	-81.0
2	66674.29	35232.85	'00:1c:b3:af:39:cb'	-94.0	'0c:27:24:e1:00:70'	-99.0
3	66672.45	35236.92	'00:1c:b3:af:39:cb'	-79.8	'0c:27:24:e1:00:70'	-92.0

Table 1: Database of the grid points with MAC-address and RSS

3.1 Online localization phase –deterministic

To check the possibility of creating a useful position from the radio-map a simple average squared deviation equation is set up:

$$\Delta dB_{TP1} = \sqrt{(dB(1)_{TP1} - dB(1)_{RTP})^2 + (dB(2)_{TP1} - dB(2)_{RTP})^2 + \dots + (dB(i)_{TP1} - dB(i)_{RTP})^2}$$

$$\Delta dB_{TP2} = \sqrt{(dB(1)_{TP2} - dB(1)_{RTP})^2 + (dB(2)_{TP2} - dB(2)_{RTP})^2 + \dots + (dB(i)_{TP2} - dB(i)_{RTP})^2}$$

$$\vdots$$

 $\Delta dB_{TPn} = \sqrt{(dB(1)_{TPn} - dB(1)_{RTP})^2 + (dB(2)_{TPn} - dB(2)_{RTP})^2 + \dots + (dB(i)_{TPn} - dB(i)_{RTP})^2}$, where $dB(i)_{TPn}$ describes the measured RSS-signal from the access point 'i' at the grid point 'n' (TPn). Each measurement in the online phase is divided into three second segments. Under the assumption that the user does not move faster than one meter per second while navigating with his smart phone, the displacement within these three seconds is not greater than three meters. Therefore the target accuracy of three meters is met for each segment. The average RSS signal within one three second segment from the same access point is calculated. Afterwards, the mac-address of the access point is compared to each point in the database. Only when a match is found, the RSS-signal from online and offline phase are compared. The compared value ΔdB_{TPn} is written into a difference vector. This vector provides information about the RSS differences between the current point and each grid point from the offline phase. The smallest entry in this vector is chosen as the position. Figures 4 show a visual representation of the discrepancies between the determined target and the actual positions. The red vectors mark the differences between actual and target points. The target position is corresponding to the nearest neighbor. When talking a closer look at Figure 4 some discrepancies between target and actual positions can be found.

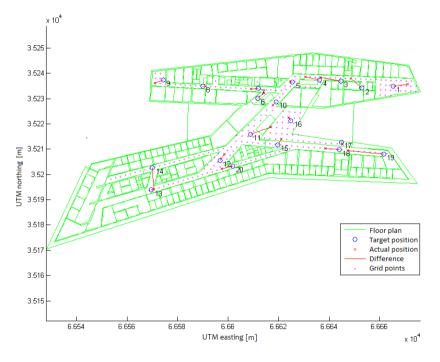


Figure 4: Deviations between actual and target positions with nearest neighbor

Development of a Wi–Fi–Fingerprinting for Position Determination by Mean of Probabilistic Methods (7600) Soeren Leitz, Friedrich Keller, Thomas Willemsen, Harald Sternberg and Steffen Kagerah (Germany)

FIG Working Week 2015 From the Wisdom of the Ages to the Challenges of the Modern World Sofia, Bulgaria, 17-21 May 2015 An attempt to improve the locations accuracy is by using not only the least deviation in the difference vector but the three least deviations. Each of the three points has a different weight for creating the new position. In Figure 5, the three corners of the blue triangle mark the three grid points with the least deviation to the offline phase measurement. The red mark is the interpolated position within the three points and their weights. Even though a few points show less deviation, the mean deviation grows by 0.4 m.

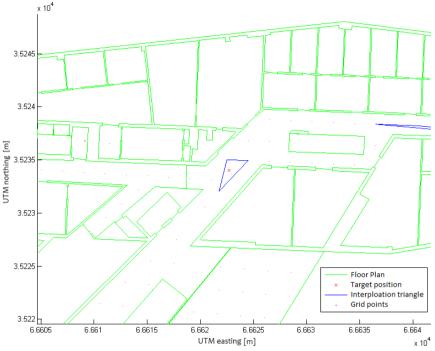


Figure 5: Positioning with interpolation triangle

3.2 Online localization phase –probabilistic

An additional probabilistic method is developed to improve the results. For this approach an occupancy grid (OG) algorithm was implemented, which originates in the Bayes' theorem. This algorithm is well known for example in the field of SLAM (Simultaneous Localization and Mapping). To generate this matrix an equidistant grid is created, which covers the floor plan of the fourth floor. Afterwards, the probability for each matrix element is inserted. Each element is updated with every measured value when creating an OG probability matrix. The grid is defined by two vectors which expand over the easting- and northing-axis of the building. An interval of one meter is chosen. To exclude points in not public areas a polygon is drawn around the floor. Within the polygons dense points are interpolated from the grid points.

To create the probability for each point, a matrix is created with the dimensions of 121×47 . Each entry in the matrix corresponds to probability of a dense point. The columns describe the easting values and the rows describe the northing values.

In the first iteration step each matrix value is set to the probability of $\frac{1}{\sum pkt}$. This probability is the inverse of the number of all dense points. In the following example with a 3 x 3

probability matrix is given to explain the functionality of the OG. The number of dense points is 3 x 3 = 9, therefore the probability for each point is set as $\frac{1}{9}$ (see Table 2). So without any further knowledge each point has the same probability of $\frac{1}{9} \approx 11$ % to be the target point.

OG	E1	E2	E3
N1	1 9	$\frac{1}{9}$	1 9
N2	1 9	1 9	1 9
N3	$\frac{1}{9}$	1 9	1 9

Table 2: First step of the probability-matrix

Afterwards, the measurement in the online phase is compared to all dense points to create a factor matrix. When no corresponding access point (by matching the MAC-addresses) is found or the RSS difference exceeds a certain threshold, a factor of 0.4 is used. A threshold of 5 dB has proven to be reasonable. When this threshold is undercut, a factor of 0.6 is used in the factor matrix. In this example the assumption is made, that two points undercut the threshold at the positions: [3,1] and [2,3]. Table 3 shows the factor matrix of the explained values.

OG	E1	E2	E3
N1	$\frac{4}{10}$	$\frac{4}{10}$	$\frac{6}{10}$
N2	$\frac{4}{10}$	$\frac{4}{10}$	$\frac{4}{10}$
N3	$\frac{4}{10}$	$\frac{6}{10}$	$\frac{4}{10}$

 Table 3: Factor matrix

In the next step the probability matrix is multiplied on a per-element basis with the factor matrix. The results are shown in Table 4. The probabilities are not multiplied by 0, due to the fact that noise or small chances can vary the RSS signal in one location. Otherwise it would be impossible to reach the dense point anymore. The probability is simply reduced by the factor 0.4.

OG	E1	E2	E3
N1	4	4	6
	90	90	90
N2	4	4	4
	90	90	90
N3	4	6	4
	90	90	90

Table 4: Probability-matrix after multiplication

Since the sum of elements in the resulting matrix is different to 1 (100%), the matrix has to be normalized. The inverse of the sum of all elements is multiplied with each value. In this example the sum of all values is $\frac{40}{90}$. Therefor the inverse of $\frac{90}{40}$ has to be set as a factor. Each value in the probability matrix is now multiplied by this factor $\frac{9}{4}$, so all probabilities sum up to one as shown in Table 5.

OG	E1	E2	E3
N1	10	10	15
1,1	100	100	100
N2	10	10	10
112	100	100	100
N3	10	15	10
113	100	100	100

 Table 5: Probability after normalization

The probability of each yellow marked position in Table 5 has 10 % probability to be the target point. With a probability of 15 % the position is now given at the two green marked values. After iterating with each RSS difference from all access points the probability of the target position changes. Ideally one element in the resulting matrix reaches a peak value close to 100 % and every other entry close to 0 %. In reality the peak value reaches up to 50 % and the surrounding points reach values of around 10 %. Due to the matrix structure short computing times are possible.

4. RESULTS AND COMPARISON

The different methods for localization are tested under real conditions during university life. For this test setup the acquired positions of 20 test points for different approaches are compared to the actual positions from the floor plan. These points are shown in Figure 4. For each point 10 seconds of measurement are performed. The deterministic and probabilistic methods are compared. The respective differences to the actual positions are stated in Table 6. All values are given with a confidence interval of 68%, due to the non-critical application purpose. In the first column of Table 6 the results of the nearest neighbor method are listed. A mean deviation of 4.5 m could be reached with this method, which is not within the accuracy goal of 3 m. As mentioned earlier, the interpolation of three points resulted in a higher mean deviation as shown in column two. The last two columns show the results of the probabilistic method. Two different interpolation methods are used to calculate the dense points, a cubic and a linear technique. The Occupancy Grid Cubic (OGC) performs well for the majority of points, but on the other hand has significant outliers. Thus the standard deviation exceeds the mean value and therefore is not significant. The Occupancy Grid Linear (OGL) has homogeneous results. Only three points exceeded a deviation of more than 5 m. This achieved accuracies also matches with other studies like Zuendt et al. (2004).

Point	Deviation to the target position with different positioning methods [m]				
Point	Interpolated	Averaged	OG Cubic	OG Linear	
1	5,9	5,9	1,8	1,6	
2	5,8	4,5	5,8	1,5	
3	8,2	8,7	6,0	3,0	
4	5,9	3,9	1,4	1,4	
5	1,0	0,7	3,4	4,2	
6	3,2	3,6	1,2	1,8	
7	2,8	4,8	1,4	1,4	
8	1,0	0,3	77,5	1,0	
9	3,4	1,7	18,4	0,9	
10	1,8	6,1	13,9	8,8	
11	8,7	6,1	7,5	2,3	
12	2,9	3,1	2,8	3,6	
13	1,1	1,1	33,5	1,3	
14	8,4	6,2	32,1	2,5	
15	2,6	6,0	4,0	2,0	
16	1,6	1,1	1,3	0,5	
17	1,0	10,5	17,7	6,3	
18	5,5	5,0	16,4	1,7	
19	14,3	16,1	48,9	5,9	
20	4,4	2,6	0,4	0,4	
avg	4,5	4,9	14,8	2,6	
std	3,4	3,8	19,8	2,2	

Table 6: Comparison of four different methods with 20 control-points: interpolated nearest neighbor, averagednearest three neighbors, Occupancy Grid cubic interpolation, and Occupancy Grid linear interpolation.(yellow = deviation > 5 m; red deviation > 10 m)

5. CONCLUSION AND OUTLOOK

The most significant insight of this project is that positioning using fingerprinting with WiFisignals is feasible. The generation of a grid for the database is vital for a successful positioning. The chosen grid distance does not only determines the size of the database but also the calculation time during the online phase. Therefore different grid distances are tested in further studies. They might be able to optimize the quality and quantity of the database. Another quality improvement might be to use more than one measurement for each point in the offline phase. As described earlier the mobile device could be faced different directions on each point. Signal noise due to the human body can be lowered, when using multiple measurements.

The investigation is based on a floor plan of one level. Therefore a simple structure can be achieved using corresponding UTM coordinates. If multiple levels need to be considered, the coordinates have to be extended by the height. Also the other levels can be measured in the offline phase with this extension. However, further studies need to investigate if the height information can successfully be determined. As a solution additional smart phone sensors such as the barometer can be used for the level detection.

If all public areas at the HCU are measured, the database would have a size about 1.3 MB. Due to the interpolation, the size of the dense points database would grow up to 10 MB. This size is still easy to handle for modern smart phones.

As shown the positioning can be performed in different ways. Further studies could focus why Zuendt et al. (2004) describe the cubic interpolation as the suitable method, even though this method performed worse at the HCU compared to the linear interpolation. Hot spots, which might occur in the dense matrix, are one possible explanation, because they become very improbable.

Even though the performance of the described methods seems very promising, they have to be considered with caution. Different transmitters or receivers might result in a different outcome. Certainty can be gained by further investigations, which use different devices and surroundings. The large amount of access points available could contribute to the good results.

The simplified test conditions might also be a cause for the good positioning with the fingerprinting methods. The limitation to one level as well to the public areas lead to short calculation times of 1 second per position with a standard computer.

The knowledge gathered in this project provides the basis for further studies. The connection of the absolute position through WiFi-fingerprinting with other relative location methods, like routing algorithms or step counters could allow a higher accuracy and reliability as well as usability. This method could allow an uninterrupted navigation from outdoors to indoors.

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