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Impact of user orientation on indoor localization based on Wi-Fi

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Abstract

Since GPS positioning is not reliable indoors due to problems with signal propagation, alternative solutions have to be used for navigation and monitoring of pedestrians as well as vehicles. The ubiquitous availability of Wi-Fi and its applicability in indoor positioning attract a lot of attention. The Wi-Fi Fingerprinting method is the most common method to estimate the localization of mobile users since its performance does not seem to be affected by multipath propagation. To compensate for the impact of the human body on signal propagation as well as irregularities in antenna gain the Orientated Fingerprinting Database was created. A built-in compass in mobile devices was used for the determination of the orientation of the user and was used as an additional parameter in the localization process. The proposed solution was tested in real-world conditions and compared with the accuracy of the system without orientation measurements. The RMSE with a compass was 4.04 m and without a compass was between 4.21 m up to 5.73 m. From the achieved results it seems that orientation information can help to improve the performance of the localization system, however, it will increase the complexity of the system deployment significantly.

Keywords: localization; orientation; fingerprinting; Wi-Fi; NN

1. Introduction

Indoor localization plays a significant role in location-based services (LBS). Indoor LBS finds vast use for instance in common buildings, garages, or airports. Typical examples are navigation for a pedestrian like navigation at the airports and shopping centers. Also, it can be applied for monitoring patients in health services, hospices as well as elderly centers. However, the application of indoor LBS is not limited to navigation and monitoring of pedestrians but can also be used for the navigation of vehicles, since GPS signals are not reliable indoors. Data

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collected from different enabling technologies can be used for indoor positioning, such as Wi-Fi (Bi et al., 2018) and (Brida et al., 2011), Bluetooth (Pušnik et al., 2020), RFID (El-Absi et al., 2020), ZigBee (Ou et al., 2017), MEMS (Huang et al., 2020), UWB (Djosic et al., 2020), a geomagnetic field (Deng et al., 2018) and (Firdaus et al., 2018). Most of these technologies require some sort of special equipment, therefore the implementation is costly. Nonetheless, Wi-Fi has a significant advantage thanks to its ubiquitous implementation as well as availability on devices.

Wi-Fi signal propagation is affected by changes in the environment, refraction, and reflection. Therefore, the quality of the signal changes with distance and environment. Most of the positioning algorithms use RSS (Received Signal Strength) measurements because RSS can be simply measured by all mobile devices equipped with a Wi-Fi receiver. This information can be processed and used for localization using either using trilateration or fingerprinting method. This paper is focused on localization using Wi-Fi signals and a fingerprinting method.

The main advantage of the fingerprinting method compared to distance-based methods is, that performance of the fingerprinting algorithms seems to be less affected by the multipath propagation of radio signal. However, the method is still influenced by the changes in the environment like changes in furniture placement, changes in the number of moving obstacles, i.e. people, vehicles, etc. Melia (2013) confirmed that the human body has an essential impact on signal propagation, and therefore affects RSS values measured by a mobile device. The impact of user orientation has become one of the targets for researchers at universities as well as in the private sector. Bi et al. (2018) proposed the adaptive weighted K-nearest neighbour fingerprinting method (AWKNN) based on the orientation fingerprint database (OFPD). In their experimental setup, 8 directions were used during collecting data for OFPD and used clustering and adjusted cluster based on transition regions. They concluded that this approach is time-consuming and inefficient. King (2006) performed positioning with 8 orientation OFPD and used a digital compass for the detection of user orientation. The OFPD was created by manually measuring RSS values. The information about the user orientation was used to choose an appropriate fingerprint from the OFPD and estimate the position of the user. There has been an application of a similar approach during the application of this technology on elderly occupants in an elderly center, proposed by Hausen and Lee (2014). Deng et al. (2018) proposed a novel approach to fingerprinting positioning, they considered users' orientation as well as the carrying position of a mobile device. The authors concluded that this approach gets better results as an approach with only the user`s orientation.

The rest of the paper is organized as follows. Section 2. describes the fingerprinting algorithm and the Euclidian algorithm using NN. In section 3. the experimental setup and achieved results are presented and analysed and section 4 will conclude the paper.

2. Background

2.1. Fingerprinting

The fingerprinting positioning framework is based on two consecutive phases. The radio map of an area of interest is generated in the first phase, which is also known as the off-line phase. In the area, spots with a known position are chosen, these spots are referred to as reference spots. On each reference spot measurements of radio signal properties, e.g. RSS, ToA, CSI, etc., are made. These measurements are then stored in the fingerprint database, also called a radio map. The off-line phase can be realized either by measurements in the location or by prediction of RSS using simulations based on radio signal propagation modelling and ray tracing (Tran and Tam, 1995). After the off-line phase follows the on-line phase when the position of a user with a mobile device at an unknown spot can be estimated based on measured signal properties. This is done by an algorithm that tries to find the best match of the measurements with data stored in the fingerprint database. This scheme of the fingerprinting method for indoor localization using Wi-Fi signals is sensitive to changes in the environment, (e. g. furniture, people, moving objects, etc.) verified by Brida et al. (2011).

An overview of the process for the fingerprinting method can be seen in Fig. 1. The Fingerprinting Database (FPD) consists of ***P[x;y]***, which represents the measured RSS values from all APs in range and is stored together with the position of each reference spot. The new measurement of an unknown spot is compared through the FPD database using the Euclidian distance. M is a number of reference spots in FPD, $\boldsymbol{Q}$ is fingerprint measured signal properties at an unknown spot.

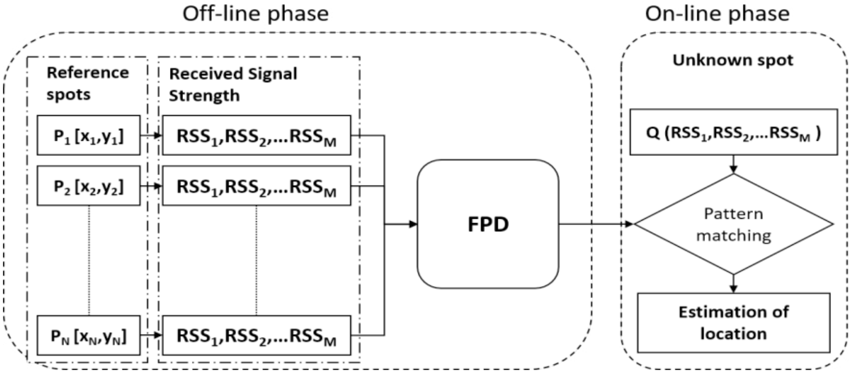

Fig. 1. Overview of the process for fingerprinting method

As will be shown later in this paper orientation of the user has a significant impact on an RSS. Therefore, in this paper, we considered the orientation of the user during the offline stage and stored measured data in an orientated fingerprinting database (OFPD). The idea behind the OFPD is to store RSS samples measured in selected orientations at each reference spot. King (2006) considered 8 orientations during assembling OFPD. However, we considered only 4 orientations, due to the time-consuming process. During the position estimation process, only RSS data with a similar orientation was used, as can be seen in Fig. 2. Each circle represents a reference spot with four signal strengths measured in each section of the circle. The measured data in the presented example are compared only with data stored in the yellow section of each reference spot.

2.2. Localization algorithm

The implemented fingerprinting localization algorithm is based on the deterministic Nearest Neighbour method and the Euclidean algorithm. The Euclidean algorithm represents the most common approach to estimate position in fingerprinting-based localization (Brida et al., 2011). Vector $\boldsymbol{P}$ interprets fingerprint in an OFPD database:

$$\boldsymbol{P} = [x_j] = [x_1, \ldots, x_M]. \tag{1}$$

In the equation, x_j includes signal characteristics of the spot and consists of measured properties (e. g. RSS). M is the amount of the signal attributes used for the creation of an FPD database.

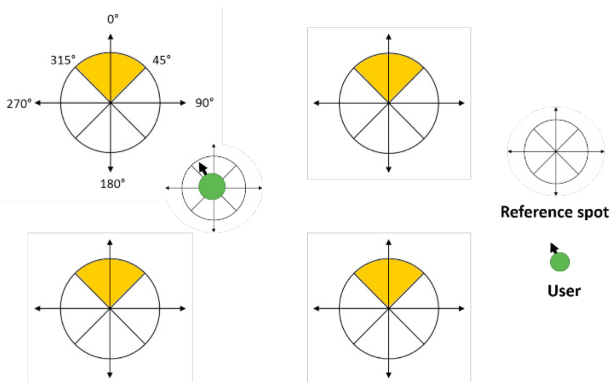

Fig. 2. Reference spots in OFPD.

$$\boldsymbol{P_i} = [x_{ij}] = [x_{i1}, \dots, x_{iM}], i = 1, \dots, N. \quad (2)$$

The FPD database contains N spots of fingerprints. The database also considers the identifier of the neighbour access point which is linked with x_j, but it is not shown there due to the simplicity of the model. The database of whole fingerprints $\boldsymbol{P_i}$ creates the set S, which can be represented:

$$S = \{P_i : i = 1 \dots N\}. \quad (3)$$

In the on-line phase was measured new signal properties and new fingerprint $\boldsymbol{Q}$ is acquired.

$$\boldsymbol{Q} = [y_j], j = 1, \dots, M. \quad (4)$$

Then formula of the Euclidian distance with a vector of distance $\boldsymbol{D}$:

$$\boldsymbol{D} = [d_i] = [|P_i - Q|] = \left[\sqrt{\sum_{j=1}^{M} (x_{ij} - y_j)^2}\right], i = 1, \dots, N. \quad (5)$$

The element of vector $\boldsymbol{D}$ with its minimum value defines the nearest reference spot to $\boldsymbol{Q}$. From all spots of reference stored in the FPD, the position of the mobile device $\hat{x}$ can be estimated by:

$$\hat{x} = \frac{\sum_{i=1}^{N} w_i \cdot p_i}{\sum_{i=1}^{N} w_i}. \quad (6)$$

Where w_i represents nonnegative weighting factor and p_i position of i-th reference spot. These weights are computed as inverse value of Euclidian distance between RSS vectors in on-line phase and vectors in FPD for i-th reference spot. If the estimator (6) keeps the K largest weights and sets the other to zero, the estimator is referred to as WKNN (Weighted K-Nearest Neighbour Method). When K-highest weights are set to $w_i = 1$ and others to 0 the method is called KNN (K-Nearest Neighbour) while the method with $K = 1$ is referred to as NN (Nearest Neighbour), which is the simplest modification (Machaj et al., 2014). It is important to note that generally WKNN and KNN can outperform the NN method, however, the difference in accuracy is reduced when the density of reference spots in the radio map gets higher.

3. Experimental setup and achieved results

The experimental scenarios were carried out in order to setup a localization system that utilizes orientation data and evaluates the effect of user orientation on the performance of the localization system. The accuracy of available orientation data from various devices was analysed in the first step. After that, a test was conducted to determine the effect of the human body on RSS measurements in various orientations, and finally, a localization system based on orientation information was implemented and tested.

3.1. Test of the accuracy of the compass in mobile devices

The test of the accuracy of the compass was performed to evaluate and prove the concept of OFPD and possible performance issues because of heterogeneous devices. Therefore, the accuracy of the compass was tested on 4 different android devices. The test was held before the first phase of the fingerprinting. Several tests have been held on devices manufactured by 3 different vendors. Table 1. shows differences in measured values, to achieve this accuracy calibration of the compass is needed before running the application. As reference values were taken values from device 1. In all the following experiments the device 1 was used for all the measurements.

From the table it can be seen that different devices report orientation with relatively small error, therefore it might be possible to use data from an electronic compass implemented in mobile devices to estimate the orientation of the device in the localization system. It is important to note that some metallic objects like a pen or a belt buckle could potentially disturb the magnetic field and cause an error in reported orientation. However, the impact of these objects is significantly reduced if the sensor implemented in the mobile device is not in their immediate vicinity.

Table 1. Test of the accuracy of the compass in mobile devices.

	Orientation [°]								average error
Device 1	271	5	17	90	159	47	250	320	reference
Device 2	266	6	20	92	162	51	254	322	3
Device 3	270	9	23	90	159	49	253	321	2.13
Device 4	275	6	18	93	163	55	252	319	3

3.2. Impact of user orientation on RSS

The second experiment aimed at the evaluation of orientation on RSS measurements was performed in the hallway in front of the room with access points AP1 and AP2. A measurement was made at the spot for 1 minute for each user's orientation. We considered 8 orientations, first direction 0°, the second direction 45°, the third direction 90°, and every time the user turned 45°. An average of 67 RSS samples was measured for each access point. The average value for RSS was calculated (7). N_s represent the number of measured samples.

$$\overline{RSS} = \frac{1}{N_s}\sum_{i=1}^{N_s} RSS_i \tag{7}$$

The human body represents a significant barrier for signal propagation due to its high consist of water for signal propagation proved by Della Rosa et al. (2012) and Melia (2013). Therefore, information about user orientation seems to be crucial for the reliable performance of a positioning system.

The mean RSS values from two different APs with the different orientations of the user are shown in Table 2, for better visualization the data are depicted in Fig. 3 as well. Signals from both APs were propagating towards the receiver in NLoS (Non-Line-of-Sight) conditions since both APs were installed in rooms and measurements were performed in the hallway.

Table 2. RSS value for the same spots with NLOS conditions for different AP.

Orientation	**0°**	**45°**	**90°**	**135°**	**180°**	**225°**	**270°**	**315°**
$\overline{RSS}[dBm]$ NLOS AP1	-81.66	-88.70	-91.49	-87.34	-91.05	-90.63	-86.89	-83.95
$\overline{RSS}[dBm]$ NLOS AP2	-86.75	-89.65	-92.38	-90.75	-94.70	-96.06	-95.22	88.41

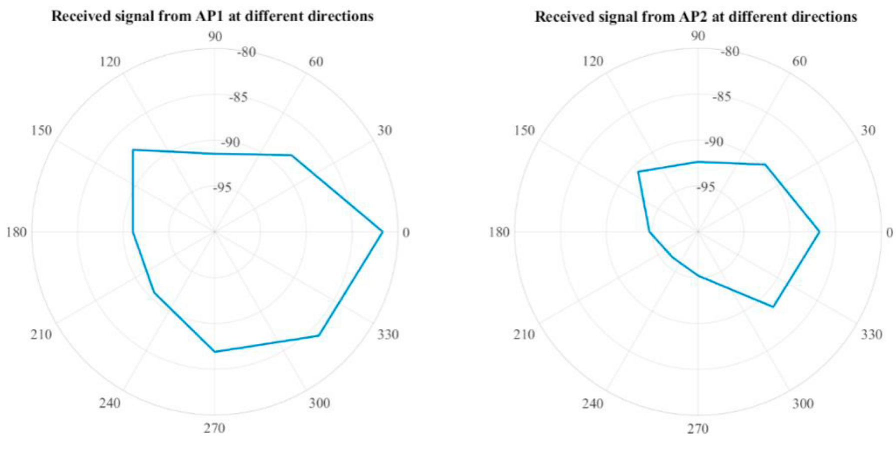

Fig. 3. Mean RSS with the different user`s orientation.

From the figure, it can be seen that the level of the RSS is affected by the user`s orientation quite significantly. The direction of 315° represents the orientation of the user towards the AP. Around this orientation, the RSS is higher since the signal is not blocked by the user. The RSS was lower in opposite directions when the signal was blocked by the user. A small increase in directions 135° and 270° was probably caused by multipath propagation. The biggest decrease in RSS was 9.61 dB for access point 1 in direction 90° and 9.31 dB for access point 2 in direction 225°.

The average decrease in RSS when the signal was fully blocked by the user was approximately 9 dB. That means the human body represents a significant barrier for signal propagation.

3.3. Localization scenario

The experiment was performed on a single floor and covers the hallway and two rooms at the Department of Multimedia and Information and Communication Technology at the University of Žilina. The hallway was covered by 32 reference spots, the first room was covered with 8 reference spots and the second room was covered with 12 reference spots. The distance between reference spots in the rooms was set to 2 meters in both directions. The distribution of reference spots in the hallway was centred and the distance between spots was 2 meters. The localization area with positions of reference spots is shown in Fig. 4.

In the off-line phase, an orientation fingerprint database was created. A measurement was made at each reference spot for a period of 10 seconds for each user's orientation. We considered 4 orientations, first direction 0°, the second direction 90°, and the third direction 180° then the fourth direction 270°. For 10 seconds an average of 10 RSS samples was measured.

For the test was used 84 access points and 52 reference spots. In each spot was measured RSS for all available access points in 4 orientations. In equation (8) the matrix for each reference spot ***a***. Then $RSS_{i\,j}$, where *i=1,2,3,4* represents the orientation of the user at 0°, 90°, 180°, and 270°, respectively. Variable *j=1,2,…, M* represents specific access points available at the reference spot. The OFPD was created with data from all 52 reference spots. During the on-line phase, the data measured by a mobile device are compared to data in OFPD with the same orientation in order to estimate the location of the user.

$$a = \begin{bmatrix} RSS_{1\,1} & RSS_{1\,2} \ldots & RSS_{1\,M} \\ RSS_{2\,1} & RSS_{2\,2} \ldots & RSS_{2\,M} \\ RSS_{3\,1} & RSS_{3\,2} \ldots & RSS_{3\,M} \\ RSS_{4\,1} & RSS_{4\,2} \ldots & RSS_{4\,M} \end{bmatrix} \tag{8}$$

During the on-line phase RSS was measured at unknown spots and data was sent to the server in vector format:

$$b = [angle \;\; RSS_1 RSS_2 \;\; \ldots \;\; RSS_M] \tag{9}$$

Angle represents the user`s orientation and RSS_j represents signal strength, where *j=1, 2,...M* represents the number of access points detected by the mobile device. In the measurements for the radio map signals from 84 different APs were received by the mobile device, on average 16 APs were detected per reference spot, while the maximum detected APs was 22 and the minimum was 5 APs.

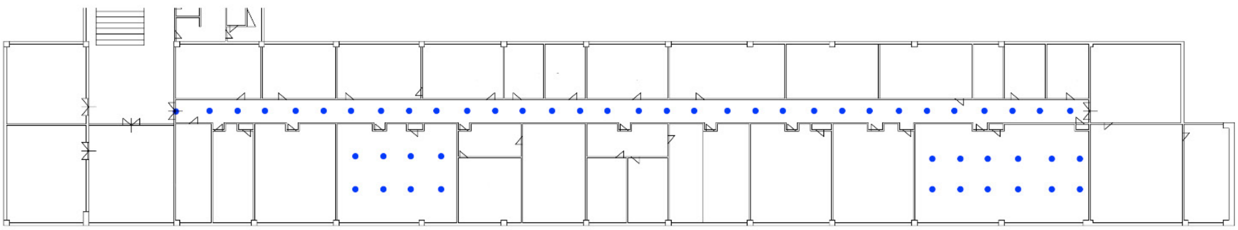

Fig. 4.The distribution of reference spots

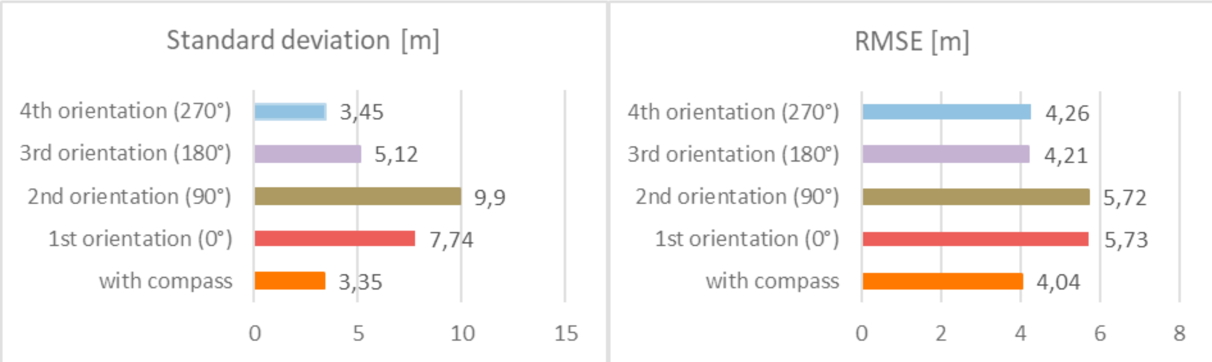

Fig.5. The comparison of the localization performance with and without a compass data

During the localization phase, the position of the mobile device was performed at 35 spots that were different from reference spots, 17 were in the hallway, and 9 for each room. Every measurement was made at all unknown spots and the value for the angle was taken from the compass application. For estimation localization was used NN algorithm and considering the user`s orientation. For choosing appropriate orientation was given range, for example, the 0° OFPD was considering when the angle was in range 314° to 45° and 0° is the mean value of the interval. So, if the angle belongs to this range, during the estimation localization algorithm considers only 0° OFPD for matching fingerprints. Error 0 was when the nearest referent spot was assigned as a user position. Otherwise, the localization error was calculated as the distance between the expected position and the estimated position. The performance of the system with orientation was compared to results achieved by the localization algorithm when fingerprints from a single orientation were used to estimate the position of the mobile device without taking its orientation into account.

We compared the system when the user`s orientation is considered, with the system without considering the user`s orientation. For the user`s localization in the system without considering the user`s orientation, 4 positions were estimated, because the RSS measurements from the deice were compared with all 4 fingerprinting databases. The results are presented in Fig.5.

The localization accuracy was the highest when data from the compass was considered during the position estimation process. The RMSE with a compass was 4.04 m and without a compass was between 4.21m up to 5.73m. The worst accuracy was obtained in the case when all localization was performed with FPD measured in the orientation of 0°. Similar results were obtained using FPD with an orientation of 90°, however, the standard deviation shows that using 90° FPD the position estimates were more spread out. In the orientation of 180°, the RMSE was close to the system with a compass however standard deviation shows that localization error was more spread out. The best results were achieved when measurements FPD created in the orientation of 270° were used, with the mean error just 5% higher compared to the system with a compass.

4. Conclusion

In this article, we have proved the human body has an impact on RSS reported by the mobile device. The experiment was held in NLOS condition and eight orientations of the user were considered. Obtained results confirmed that the human body represents a significant barrier for signal propagation. The average decrease in RSS when the signal was fully blocked by the user`s body was approximately 9 dB. Therefore, we implemented and verified a positioning solution based on OFPD. The measurement of RSS was based on IEE 802.11 standard considering the user`s orientation.

For creating the OFPD the user`s orientation needs to be considered, therefore a test of the accuracy of the compass in mobile devices was held. Achieved results show a relatively small error between orientations reported by different devices, therefore, it is possible to use data from the electronic compass implemented in mobile devices to estimate the orientation of the device.

Comparison of the localization system considering the user`s orientation with a system without considering the user`s orientation shows that the user`s orientation has an impact on the accuracy of position estimation. RMSE and standard deviation show that when considering the user`s orientation RMSE we get the highest accuracy among the obtained results. However, the process of creating OFPD was time-consuming and gained improvement in the accuracy was not significant.

Future work will be aimed at further investigation of orientation on performance of localization system in order to gain a deeper understanding of how including orientation information could help improve localization performance without a significant increase in complexity of radio map.

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