Wi-Fi Azimuth and Position Tracking: Signal Propagation, Modeling and Evaluation

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Abstract—Tracking algorithms for estimating and tracking the azimuth angle regarding north and a two-dimensional position of a mobile unit carried by a pedestrian are presented. Outdoors, the azimuth angle of a device can be easily detected using an electronic compass. The position can be calculated using a global navigation satellite system. Indoors, magnetic disturbances lead to unreliable compass outputs. Also, indoors there exists no standard positioning system. Using Wi-Fi signal strength measurements the position of a receiver can be tracked using so called fingerprinting methods. If the signal strengths measurements are collected with directional antennas additionally the azimuth can be tracked. For the presented tracking filters we extended Wi-Fi based Markov localization algorithms for evaluating directional antennas to calculate azimuth besides position. Furthermore, these techniques have been adapted to use a particle filter for the estimation. Well known Wi-Fi fingerprinting approaches are included in the measurement models and pedestrian dead reckoning in the prediction models. Measurements have been collected inside and outside of an office building to evaluate the performance of the different tracking algorithms. Especially in indoor environments these approaches facilitate the use of electronic guides that offer additional information by means of augmented reality, e.g. on museum exhibits in visual range.

I. INTRODUCTION

Modern smart phones are equipped with a variety of sensors. For positioning, satellite receivers, GSM (Global System for Mobile Communications), UMTS (Universal Mobile Telecommunications System) and wireless LAN (Local Area Network) modules can be used. Based on them, new and cheap approaches to pedestrian navigation can be provided. This enables new types of location based services for pedestrians ranging from calls for taxis, finding points of interests to city and museum guides.

Commonly the first choice for navigation is the Global Positioning System (GPS). However, the lack of precision and availability of GPS in urban and indoor environments is a prevalent problem. As an alternative or complementary solution for indoor environments Bahl et al. [1] suggested a positioning approach based on the received signal strength (RSS) in Wi-Fi™ [2] networks. Nowadays, because of an increasing number of public and private base stations [3], Wi-Fi positioning becomes more and more attractive for navigation and is already integrated into many smart phones. One remaining challenge is estimating the heading, or better the pose, of a person. Pedestrians move very slowly and can turn anytime without changing their position. So, the speed vector of a pedestrian calculated from consecutive positions has a very low accuracy. The positioning accuracy can be improved by combining Wi-Fi positioning with dead reckoning, using low cost sensors and Hidden Markov models, as proposed in [4], [5]. For pedestrians, dead reckoning can be improved by step detection, as analyzed in [6]. But, estimating the heading is still challenging. Utilizing only Wi-Fi signals Tayebi et al. presented in [7] an approach using ray tracing simulations for an indoor environment to predict the directions of arrival (DOA) of Wi-Fi signals. DOA fingerprints from simulations are compared to measured DOAs. However, this approach is not feasible with standard Wi-Fi hardware. In [8] Röhrig et al. extended Wi-Fi fingerprinting by using an additional directional antenna to estimate the horizontal pose of a mobile robot. In that case, the estimation results depend strongly on the placement of the base stations and degrade in presence of strong multipath components.

In [9] we presented an algorithm based on an extended Kalman filter to track line of sights to Wi-Fi base stations in order to estimate the horizontal pose of pedestrians. Instead of various sensors a special antenna setup with four directional antennas was used. In [10] we used the same setup together with a multipath propagation model to estimate the azimuth and position. The well-known fingerprinting approach for Wi-Fi positioning using the Euclidean distance in signal space has been adopted to evaluate directional RSS measurements. In this paper we evaluate this approach together with new approaches based on the Hidden Markov models presented in [4] and [5], and new approaches based on particle filters. In Sec. II underlying physical models for signal propagation in multipath environments are recapitulated and a brief introduction to Wi-Fi positioning is given. In Sec. III the fingerprinting algorithms for evaluation are defined and evaluated in Sec. IV with measurement data collected inside and outside of a typical office building.

II. SIGNAL PROPAGATION AND WI-FI POSITIONING

In this section we give an overview on Wi-Fi positioning and discuss the influence of signal propagation in different environments on Wi-Fi positioning. Finally, assumptions made performing Wi-Fi positioning using fingerprinting methods are highlighted.

A. Wi-Fi Positioning

Wi-Fi positioning is based on received signal strength (RSS) measurements collected by mobile devices. Wi-Fi positioning methods can be divided into two groups. The first
group needs a database with positions and signal strengths of known Wi-Fi base stations, e.g. [11] and [12], and the second group needs a database of so-called fingerprints, e.g. [1] and [13]. Our approach, awiloc® [14], for seamless citywide indoor and outdoor positioning belongs to the second group. Reasons for choosing this approach are that fingerprinting is reported to achieve higher precision than base station based methods and generally positions of base stations are not public. As reported in [3] and [15], several methods are used to collect the measurements to build up the fingerprinting database. To get meaningful Wi-Fi positioning results, in practice at least three base stations must be observed. An advantage of Wi-Fi positioning in urban environments is that the infrastructure is already set up. Existing private and public base stations can be used. In Fig. 1 a part of the awiloc® [14] database covering the city center of Nuremberg is presented. There, on average a recorded fingerprint contains 21 base stations.

The RSS at a specific position \( \chi = [x, y, z]^T \) depends mainly on path loss, shadowing by objects and multipath propagation. The COST231 multi-wall model [16] is widely used to create a database of fingerprints based on simulations instead of manual measurements. It considers path loss and shadowing by walls, floors or large objects. In Fig. 2a the signal propagation in an office environment is depicted: One wave front has a complex amplitude \( A \) and phase \( \psi \). The baseband representation \( u(\chi) \) can be modeled using wavenumber \( k = 2\pi\frac{\lambda}{\lambda_0} \cdot e \), with the wave length \( \lambda \) and the unit vector of the arriving wave \( e \):

\[
u(\chi) = A e^{-j k \cdot \chi}
\]

Using RSS measurements at arbitrary positions the parameters \( \eta \) and \( a_k \) can be tuned for individual buildings [17]. Positions with the same distance \( d(\chi) \) to a base station \( i \) can have a different \( P_{Rx,i}(\chi) \) if different objects or a different amount of objects are on the path. The higher the density of shadowing objects and base stations, the less similar are fingerprints in signal space, and the higher is the accuracy of Wi-Fi positioning. Therefore, indoors Wi-Fi positioning works very well. Outdoors, especially on large squares, the database correlation results in ambiguities, as presented in [5]. Changes of physical structures in the environment and moving shadowing objects, like cars and persons, are not considered and therefore limit the accuracy and can lead to temporarily higher positioning errors. An analysis of database changes can be found in [3].

\[
P_{Rx,i}(\chi) = P_{Tx,i}(d_0) - 10 \eta \log \left( \frac{d(\chi)}{d_0} \right) + G_{Rx} - \sum_{k=1}^{N_{Obj}} n_k a_k
\]

\[
F_{Rx,i}(\chi) = 20 \log \left( \sum_{w=1}^{N_{WF}} u_w(\chi) \right) + c
\]
Following, we examine the planar two-dimensional case with $\varphi = \omega = 0$. In Fig. 3a and Fig. 3c two exemplary interference heat maps for six arbitrary wave fronts are depicted. In simulations (3) has been evaluated for a square area with a side length of $2\lambda$. In Fig. 3c signal degradations of up to 60 dB can be observed. In absence of a dominant path this is caused by destructive interference. With a dominant path in Fig. 3a the impact of this effect is much less. The amplitudes $A_x$ and DOAs $\phi_w$ of the used six wave fronts are indicated by crosses in Fig. 3b and Fig. 3d. Usually multipath propagation is not modeled for Wi-Fi positioning. But, consecutive measurements are collected and filtered to reduce especially the effect of local signal degradations. The more measurements are collected at each fingerprint location, the better the filtered RSS measurements to the database entries. The size of each fingerprint location depends on changes in the slow fading situation. Therefore, indoors the area size is generally much smaller than outdoors, but a lot larger than the Wi-Fi wave length of $\lambda = 12.0$ cm ... $12.5$ cm. Indoors 0.5 m up to 3 m and outdoors 3 m up to 20 m are common sizes of fingerprint locations.

In the following we generalize (3) for the use of arbitrary antennas to collect the RSS measurements. If directional antennas are used in the mobile unit each wave front is weighted by a factor. In the planar two-dimensional case the weight factor $w_w(\varphi)$ for each wave front $w \in \{1 \ldots N_{WF}\}$ depends on the DOA $\phi_w$ and on the azimuth angle $\varphi$ of the antenna:

$$P_{Rx,i}(x,y,\varphi) = 20 \log \left( \frac{N_{WF}}{\sum_{w=1}^{N_{WF}} w_w(\varphi, \phi_w) u_w(x,y)} \right) + c$$

So, all wave fronts are combined differently at the same position $X = [x, y]^T$ depending on the azimuth of the antenna $\varphi$. To calculate the weight factor of the antenna $w(\varphi)$ a polar equation is used in the simulations:

$$w(\varphi, \phi) = A + B \cos(\varphi - \phi)$$

$A$ is the isotropic part and $B$ the dipole part of the antenna, e.g. with $A = 1$ and $B = 0$ we get an omni-directional antenna, with $A = 0$ and $B = 1$ a dipole.

Using directional antennas, each directional reference RSS value $P_{Rx,ref,i}(l_x,l_y,\varphi_{ref})$ in the fingerprinting database is the mean of all $N_x$ directional RSS values collected at a fingerprint location $l = [l_x,l_y]^T$ with the same azimuth angle $\varphi_{ref}$:

$$P_{Rx,ref,i}(l_x,l_y,\varphi_{ref}) = \frac{1}{N_x} \sum_{n=1}^{N_x} P_{Rx,i}(x_n,y_n,\varphi_{ref})$$

We call $P_{Rx,ref,i}(l_x,l_y,\varphi_{ref})$ the angular RSS characteristic of base station $i$ at the fingerprint location $l$. In Fig. 3b and Fig. 3d two exemplary angular RSS characteristics from simulations are presented. Without a dominant path in Fig. 3d the characteristic depends on the distribution of the angles of arrival. In presence of a dominant path in Fig. 3b the angular RSS characteristic reflects the polar equation in (5) with $A = 0.6$ and $B = 0.4$. Exemplary directional heat maps of angular RSS characteristics are depicted in Fig. 4 and Fig. 5 with and without the dominant path. In Fig. 4 compared to Fig. 3a it can be seen, that with $\varphi = 180^\circ$ due to the antenna loss the amplitude of the dominant path is in the order of the other paths. So, the interference heat map in Fig. 4c looks more like the one in Fig. 3c for no dominant path. In Fig. 5 compared to Fig. 3c the shapes of the directional interference heat maps are different but similar.
A. Euclidean Fingerprinting

For Euclidean fingerprinting we use \( x_t = [x_t, y_t, \varphi_t]^T \) as our state vector including a two-dimensional position \( [x, y]^T \) and the azimuth angle \( \varphi_t \) of the antenna setup. The RSS \( P_{\text{Rx},i}(x_t, y_t, \varphi_t) \) of base station \( i \) can be measured simultaneously with multiple directional antennas to improve estimation. Each directional antenna \( n \) has an antenna heading \( \vartheta_n \), relative to the azimuth angle of the device \( \varphi_t \). So, \( P_{\text{Rx},i}(x_t, y_t, \varphi_t) \) becomes \( P_{\text{Rx},i}(x_t, y_t, \varphi_t + \vartheta_n) \). We define a measurement vector \( h_i(x_t) \) of single RSS measurements \( h_{t,i,n} \) for all received base stations \( i \in \{1, \ldots, N_{\text{BS}}\} \) and all antennas of the measurement setup \( n \in \{1, \ldots, N_{\text{Ant}}\} \):

\[
 h_i(x_t) = \begin{bmatrix}
 h_{t,1,1} \\
 h_{t,1,2} \\
 \vdots \\
 h_{t,1,N_{\text{Ant}}} \\
 h_{t,2,1} \\
 \vdots \\
 h_{t,N_{\text{BS}},N_{\text{Ant}}} \\
 h_{t,N_{\text{BS}},N_{\text{Ant}}} 
\end{bmatrix} = \begin{bmatrix}
 P_{\text{Rx},1}(x_t, y_t, \varphi_t + \vartheta_1) \\
 P_{\text{Rx},1}(x_t, y_t, \varphi_t + \vartheta_2) \\
 \vdots \\
 P_{\text{Rx},1}(x_t, y_t, \varphi_t + \vartheta_{N_{\text{Ant}}}) \\
 P_{\text{Rx},2}(x_t, y_t, \varphi_t + \vartheta_1) \\
 \vdots \\
 P_{\text{Rx},N_{\text{BS}}}(x_t, y_t, \varphi_t + \vartheta_{N_{\text{Ant}}}) 
\end{bmatrix}
\]

E.g. a measurement vector \( h_i(x_t = 5 \text{ m}, y_t = 1 \text{ m}, \varphi_t = 0^\circ) \) collected at position \( [5 \text{ m}, 1 \text{ m}]^T \) with an azimuth angle of \( 0^\circ \) of the setup, measured with four directional antennas with \( \vartheta_n \in \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \), is defined as follows:

\[
 h_i(5 \text{ m}, 1 \text{ m}, 0^\circ) = \begin{bmatrix}
 P_{\text{Rx},1}(5 \text{ m}, 1 \text{ m}, 0^\circ) \\
 P_{\text{Rx},1}(5 \text{ m}, 1 \text{ m}, 90^\circ) \\
 P_{\text{Rx},1}(5 \text{ m}, 1 \text{ m}, 180^\circ) \\
 P_{\text{Rx},1}(5 \text{ m}, 1 \text{ m}, 270^\circ) \\
 P_{\text{Rx},2}(5 \text{ m}, 1 \text{ m}, 0^\circ) \\
 P_{\text{Rx},2}(5 \text{ m}, 1 \text{ m}, 90^\circ) \\
 P_{\text{Rx},2}(5 \text{ m}, 1 \text{ m}, 180^\circ) \\
 P_{\text{Rx},2}(5 \text{ m}, 1 \text{ m}, 270^\circ) \\
 \vdots 
\end{bmatrix}
\]

As a straightforward approach for estimating the horizontal pose using directional RSS measurements we use the well-known Wi-Fi fingerprinting based on the normalized Euclidean distance in signal space, e.g. [1]. We adopted this fingerprinting approach for pose estimation with directional antennas in [10]. Firstly, we have to set up a database of fingerprints. Secondly, we can estimate the pose. Using multiple directional antennas instead of one omnidirectional antenna the fingerprinting database increases in dimensionality. For conventional Wi-Fi positioning one heat map is created for each base station in range, see Fig. 3. For horizontal pose estimation one heat map is created for each base station in range and additional for each directional antenna in the antenna setup, see Fig. 4 and Fig. 5. A RSS vector in the database \( h_{\text{ref}}(x_{\text{ref}}) \) for a fingerprint location \( l = [x_l, y_l]^T \) is created using (6) by calculating the mean of all measurements collected within \( l \) with the same azimuth angle \( \varphi_{\text{ref}} \) of the directional antenna. To be able to evaluate more azimuth angles than stored in the database the database is interpolated. We perform a linear interpolation of the stored angular RSS characteristic \( P_{\text{Rx},\text{ref},i}(x_{\text{ref}}) \) defined in (6), for each received base station \( i \) at each fingerprint position \( l \). \( h_{\text{ref}}(x_{\text{ref}}) \) is then the interpolated vector of the stored database entries at \( l \) for azimuth angle \( \varphi_{\text{ref}} \) in Fig. 6 two examples of linear interpolated angular RSS characteristics are
given. The fit of the interpolated angular RSS characteristic at a fingerprint position depends on the incoming wave fronts and on the amount and the selection of antenna heading angles.

For pose estimation an equivalence measure is calculated for each fingerprint \( \mathbf{x}_{\text{ref}} \). We calculate the normalized Euclidean distance in signal space of the measured RSS vector \( \mathbf{h}_t(\mathbf{x}_t) \) at time \( t \) and the database vectors \( \mathbf{h}_{\text{ref}}(\mathbf{x}_{\text{ref}}) \). The final pose estimate \( \hat{x}_t \) is then the pose \( \mathbf{x}_{\text{ref}} \in \mathbf{X}_{\text{ref}} \) in the database with the minimum Euclidean distance:

\[
\hat{x}_t = \arg \min_{\mathbf{x}_{\text{ref}} \in \mathbf{X}_{\text{ref}}} \left\{ \frac{1}{\mathbf{N}_{\text{RSS}} \mathbf{N}_{\text{Ant}}} \left\| \mathbf{h}_t(\mathbf{x}_t) - \mathbf{h}_{\text{ref}}(\mathbf{x}_{\text{ref}}) \right\|^2 \right\},
\]

with: \( \| \cdot \| = \sqrt{(\mathbf{h}_t(\mathbf{x}_t) - \mathbf{h}_{\text{ref}}(\mathbf{x}_{\text{ref}}))^T(\mathbf{h}_t(\mathbf{x}_t) - \mathbf{h}_{\text{ref}}(\mathbf{x}_{\text{ref}}))} \)

The distance in signal space is normalized by the total number of received base stations \( \mathbf{N}_{\text{RSS}} \) and directional antennas in the setup \( \mathbf{N}_{\text{Ant}} \). The proof of concept of directional Euclidean fingerprinting has been presented in [10].

### B. Markov Localization

We extend the approved Markov localization presented in [5] to estimate the horizontal pose \( \mathbf{x}_t = [x_t, y_t, \phi_t]^T \) instead of only the user position \( [x_t, y_t]^T \). As for fingerprinting the proposed Markov localization is based on a discrete fingerprint grid with discrete positions and azimuth angles. So, only fingerprint poses are evaluated as possible poses. Interpolation of the angular RSS characteristics to create more fingerprint poses is applied, too. The iterative estimation process is divided into two steps: the movement update and the RSS update. The movement update is based on the Markov assumption that the pose \( \mathbf{x}_t \) at time \( t \) depends only on the previous pose \( \mathbf{x}_{t-1} \) and the last movement \( \mathcal{M}_t \). It is independent of the previous movements \( \mathcal{M}_{t-1} \) and the previous RSS measurements \( \mathcal{R}_{t-1} \). For all possible poses \( \mathbf{x}_t \in \mathbf{X}_t \) at time \( t \) a probability distribution is calculated, that is the transition probability distribution \( p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathcal{M}_t) \) weighted by the previous probability distribution \( p(\mathbf{x}_{t-1}|\mathcal{M}_{t-1}, \mathcal{R}_{t-1}) \):

\[
p(\mathbf{x}_t|\mathcal{M}_t, \mathcal{R}_{t-1}) = \sum_{\mathbf{x}_{t-1} \in \mathbf{X}_{t-1}} p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathcal{M}_t) \cdot p(\mathbf{x}_{t-1}|\mathcal{M}_{t-1}, \mathcal{R}_{t-1})
\]

The transition probability distribution is calculated according to [5] using the heading of a pedestrian \( \Phi_t \) and the distance \( \mathcal{D}_t \) as movement \( \mathcal{M}_t \). Under the assumption that heading and distance walked are independent of each other, the movement update can be written as:

\[
p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathcal{M}_t) = p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathcal{D}_t, \Phi_t) = p(\mathcal{D}_t|\mathbf{x}_t, \mathbf{x}_{t-1}) \cdot p(\Phi_t|\mathbf{x}_t, \mathbf{x}_{t-1}) \cdot p(\mathbf{x}_t|\mathbf{x}_{t-1})
\]

(11)

According to [5], additional sensor data, e.g. from an electronic compass and accelerometers for step detection of a pedestrian, can be used in the movement update to calculate heading and distance walked. Indoors magnetic disturbances caused, e.g. by building structure, can lead to unreliable compass outputs. We are not using an electronic compass, as in contrast to [5] the azimuth of the receiver is estimated using directional RSS measurements. In Eq. (11) the probability distributions characterizing the distance and angle measurements and are assumed to be Gaussian with variances \( \sigma_d \) for distance and \( \sigma_\phi \) for heading. The estimated distance traveled \( d_t \) is compared to the distance between the current and previous position \( d(\mathbf{x}_t, \mathbf{x}_{t-1}) \), as mean of the distribution, similar to [5]:

\[
p(\mathcal{D}_t = d_t|\mathbf{x}_t, \mathbf{x}_{t-1}) = p(\mathcal{D}_t = d_t|\mathbf{x}_t, \mathbf{x}_{t-1}) = \frac{1}{\sqrt{2\pi} \cdot \sigma_d} \cdot e^{\frac{-d_t^2}{2\sigma_d^2}}
\]

(12)

But instead of using a compass, the estimated heading \( \phi_t \) is compared to the heading between the current and the previous position \( \phi(\mathbf{x}_t, \mathbf{x}_{t-1}) \), as mean of the distribution:

\[
p(\Phi_t = \phi_t|\mathbf{x}_t, \mathbf{x}_{t-1}) = p(\Phi_t = \phi_t|\mathbf{x}_t, \mathbf{x}_{t-1}) = \frac{1}{\sqrt{2\pi} \cdot \sigma_\phi} \cdot e^{\frac{-(\phi_t - \phi(\mathbf{x}_t, \mathbf{x}_{t-1}))^2}{2\sigma_\phi^2}}
\]

(13)

In the RSS update we calculate the probability distribution \( p(\mathbf{x}_t|\mathcal{M}_t, \mathcal{R}_t) \) for the poses \( \mathbf{x}_t \) given all movements \( \mathcal{M}_t \) and RSS measurements \( \mathcal{R}_t \) up to time \( t \). The probability distribution \( p(h_t|\mathbf{x}_t) \) calculated using the collected RSS measurement vector \( h_t \) is weighted by the probability distribution of the movement update from (11) and normalized:

\[
p(\mathbf{x}_t|\mathcal{M}_t, \mathcal{R}_t) = \frac{\sum_{\mathbf{x}_t} p(h_t|\mathbf{x}_t) \cdot p(\mathbf{x}_t|\mathcal{M}_t, \mathcal{R}_t)}{\sum_{\mathbf{x}_t} p(h_t|\mathbf{x}_t) \cdot p(\mathbf{x}_t|\mathcal{M}_t, \mathcal{R}_t-1)}
\]

(14)

For \( p(h_t|\mathbf{x}_t) \) we adapt the probabilistic database correlation presented in [17] and [5]. A Gaussian distribution with a standard deviation \( \sigma_h \) is assumed for each RSS measurement at a fingerprint location \( l \). Similar to (9), but now in a probabilistic manner, the current measurements \( h_t(\mathbf{x}_t) \) are compared to the database entries \( h_{\text{ref}}(\mathbf{x}_{\text{ref}}) \). As typically Wi-Fi devices provide discrete RSS values quantized within an interval of approximately 1 dB, we integrate the probability density function between \( a = h - 0.5 \) dB and \( b = h + 0.5 \) dB:

\[
p(h_t|\mathbf{x}_t) = \frac{1}{\sqrt{2\pi} \cdot \sigma_h} \cdot \int_a^b \frac{1}{2\sigma_h} \cdot e^{\frac{-d_t^2}{2\sigma_h^2}} \, dh
\]

(15)

The final user pose \( \hat{x}_t \) can be estimated by calculating the weighted mean of all possible poses \( \hat{x}_t \), weighted by (14).
C. Particle Filter

In contrast to the two presented approaches the following particle filter is based on a continuous state space. Particle filters are sequential Monte Carlo methods based on point mass representations of probability densities called particles. More details on particle filters can e.g. be found in [20]. For tracking pedestrians we use particles with state vector \( \hat{x}_t = [\hat{x}_t, \hat{y}_t, \hat{\phi}_t, \hat{d}_t]^T \), containing horizontal position, azimuth and walked distance \( d_t \) since the last filter update. \( j \) is the particle index with \( j \in \{1, \ldots, N_P \} \) and the total number of particles used \( N_P \). We choose this state vector instead of using the two-dimensional position and velocity as states to be closer to pedestrian dead reckoning based on detected steps, step length estimation and heading measurements.

To estimate the horizontal pose a sampling importance resampling (SIR) filter is used, as defined in [20]. The iterative filter is divided into the following steps: initialization of particles, interpolation of database entries, calculation of particle weights using directional RSS measurements, systematic resampling of particles and sampling of particles using a pedestrian dead reckoning motion model. The final user pose \( \hat{\mathbf{x}}_t \) can be estimated similar to Sec. III-B by calculating the weighted mean of all possible poses \( \mathbf{x}_t \), weighted by the particle weights. The filter is initialized with uniformly spread particles in the particle space. The two dimensional position space is limited by our local map of fingerprint positions, the azimuth can be within \([0^\circ, 360^\circ]\) and the distance traveled can be within \([0 \text{m}, d_{\text{max}}]\). The maximum travel distance \( d_{\text{max}} \) depends on velocities of pedestrians and the time since the last filter update, e.g. \( d_{\text{max}} = 5 \text{m/s} \cdot \Delta t \).

To calculate the particle weights each particle \( \hat{\mathbf{x}}_t \) needs to be mapped to a fingerprint pose. Herein, we simply select the fingerprint with the minimum distance in position to the particle and for the azimuth of the particle we interpolate the database entries to get \( h_{\text{ref}}(\mathbf{x}_{\text{ref}}) \), as defined above. So, the particle position is unchanged, but the RSS measurements \( h_t \) are evaluated using the nearest fingerprint pose \( h_{\text{ref}}(\mathbf{x}_{\text{ref}}) \). Then, the weight \( w_t^j(h_t|\hat{\mathbf{x}}_t^j) \) of each particle \( \hat{\mathbf{x}}_t^j \) can be calculated in the same way as in (15):

\[
\tilde{w}_t^j(h_t|\hat{\mathbf{x}}_t^j) = \frac{1}{\sqrt{2\pi} \cdot \sigma_{\text{RSS}}} \cdot \int_a^b e^{-\frac{1}{2\sigma_{\text{RSS}}^2} (||h_t(x_t) - h_{\text{ref}}(x_{\text{ref}})||)^2} \, dh
\]

After the weights have been updated the resulting weights need to be normalized by the sum of the weights:

\[
w_t^j(h_t|\hat{\mathbf{x}}_t^j) = \frac{\tilde{w}_t^j(h_t|\hat{\mathbf{x}}_t^j)}{\sum_{j=1}^{N_P} \tilde{w}_t^j(h_t|\hat{\mathbf{x}}_t^j)}
\]

We use systematic resampling to eliminate particles with low weights and multiply particles with high weights to get an unweighted probability density function. For systematic resampling \( N_P \) ordered numbers are generated and used with the particle weights to generate new particles having the same weight \( w_t^j(h_t|\hat{\mathbf{x}}_t^j) = \frac{1}{N_P} \), as proposed in [20].

When new directional RSS measurements are available the particles need to be sampled first before the weights can be updated again. We use pedestrian dead reckoning for sampling the particles. Firstly, we sample the azimuth of each particle \( \hat{\phi}_t^j \) using a random walk model with \( (\hat{\phi}_t^{j-1} + \delta_{\phi}) \sim N(\hat{\phi}_t^j, \sigma_{\phi}) \) and the walked distance \( d_t^j \) using control input \( d_{\text{t,step}} \) and \( \delta_d \):  

\[
\begin{bmatrix} \hat{\phi}_t^j \\ d_t^j \end{bmatrix} = \begin{bmatrix} \hat{\phi}_t^{j-1} \\ d_{\text{t,step}} \end{bmatrix} + \begin{bmatrix} \delta_{\phi} \\ \delta_d \end{bmatrix}
\]

The walked distance can be estimated using step detection and step length estimation based on accelerometer data as e.g. analyzed in [6]. In this case the walked distance \( d_{\text{t,step}} \) is the sum of all step lengths of detected steps since the last filter step. If no step information is available a constant mean for the walked distance between two consecutive filter iterations can simply be assumed. Secondly, for each particle its new position is calculated using the old particle position as starting position and adding the sampled walked distance \( d_t^j \) in direction of the sampled azimuth \( \hat{\phi}_t^j \):

\[
\begin{bmatrix} \hat{x}_t^j \\ \hat{y}_t^j \end{bmatrix} = \begin{bmatrix} \hat{x}_{t-1}^j \\ \hat{y}_{t-1}^j \end{bmatrix} + \begin{bmatrix} d_t^j \cos(\hat{\phi}_t^j) \\ d_t^j \sin(\hat{\phi}_t^j) \end{bmatrix}
\]

Finally, the filter iteration is completed and the new weights for the sampled particles can be calculated using the next RSS measurements.

IV. EXPERIMENTAL RESULTS

To evaluate the presented tracking algorithms commercial available components have been used. Four directional patch antennas [21] in a setup with \( \vartheta_n \in \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \) have been connected to four USB Wi-Fi adapters [22]. One additional bar antenna has been connected to a fifth USB Wi-Fi adapter and is used for standard fingerprinting as a state-of-the-art positioning reference. One inertial measurement unit (IMU) is plugged to the antenna module to monitor the changes of the azimuth of the antenna module. Another module is placed for step detection at the center of mass (COM) of the pedestrian. The Antenna module with the inertial sensor is attached to a bicycle helmet. Therefore, it is easy to carry it and the antennas are placed above head to blank out the effects of the human body on signal propagation in this evaluation. The measurement environment is shown in Fig. 7. Measurements have been collected on the ground floor inside and outside of an office building. The reference poses for the entries in the fingerprinting database and the reference poses for evaluating the measurements have been determined in the following way. Marks on the floor indicate positions where the time was manually recorded during walking to create waypoints with time stamps. Steps have been detected using the IMU acceleration data measured at the COM of the pedestrian. Using the number of steps between waypoints, assuming a constant speed, the positions after each step can be estimated. A reference for the azimuth of the antenna setup has been estimated by integration of the gyroscope measurements of the IMU plugged to the antenna module together with a known azimuth at start of each path. The resulting fingerprints, clustered roughly with a spacing of 2m, are shown in Fig. 7a as gray squares. Fingerprints have been collected in all accessible rooms in the upper part of Fig. 7a, in the corridors inside the ground floor and outside of the building on sidewalks. After setting
Standard fingerprinting, directional fingerprinting and Markov localization are fixed to the fingerprint positions, because the fingerprints are used by them as a discrete state space. Estimated poses are in between, or near high probabilities, because they are calculated by weighted means of the poses with the highest probabilities. For standard fingerprinting in Fig. 8a only the position can be estimated, an arrow indicating the azimuth is missing. If the estimation results have ambiguities this can lead to jumps of the estimated positions to ambiguous fingerprints, as can be seen in Fig. 8a and Fig. 8b. For Markov localization in Fig. 8c with the pedestrian dead reckoning model in the movement update ambiguities can be reduced. In contrast, the particle filter in Fig. 8d is based on a continuous state space. So, the probability distribution, the particle cloud, is formed around the estimated pose, if no strong ambiguities remain. Furthermore, the estimated track is not fixed to the fingerprint positions. Again, the pedestrian dead reckoning model used for sampling the particles reduces ambiguities.

For evaluation, the measurement data collected three times on the path in Fig. 7b has been processed. While the estimation results using standard fingerprinting, directional fingerprinting and Markov localization on the same measurement data are deterministic, the stochastic nature of particle filters results in varying estimation results. Therefore, using a particle filter the measurement data has been processed several times. The resulting estimation errors as percentile curves are presented in Fig. 9. As expected, concerning Sec. II-B, standard fingerprinting performed worst, because no directional information is available. Consequently, no azimuth can be estimated. Directional fingerprinting and Markov localization have similar estimation results. Both are based on a discrete grid, but Markov localization uses a movement model to predict the next states. It looks like in the selected environment only insignificant ambiguities evaluating the RSS measurements occurred. Using the particle filters best estimation results could be achieved. For estimation 1000 particles have been used. With this number of particles the computation time is similar to using directional fingerprinting or Markov localization. But, using step detection did not improve the results in this case. On the one hand, step detection can improve the particle sampling. On the other hand, we had to use a large standard deviation while sampling with the step lengths to prevent the particle filter from getting lost for a period of time until starting to track the pose again. Nevertheless, the presented SIR particle filter is a simple standard particle filter and there is space for

The estimation results of the algorithms presented in Sec. III have different characteristics. In Fig. 8a a snapshot of the estimated tracks and poses after the evaluation of RSS measurements is presented. The probability distributions for standard fingerprinting, directional fingerprinting and Markov localization are presented in Fig. 9. As expected, concerning Sec. II-B, standard fingerprinting performed worst, because no directional information is available. Consequently, no azimuth can be estimated. Directional fingerprinting and Markov localization have similar estimation results. Both are based on a discrete grid, but Markov localization uses a movement model to predict the next states. It looks like in the selected environment only insignificant ambiguities evaluating the RSS measurements occurred. Using the particle filters best estimation results could be achieved. For estimation 1000 particles have been used. With this number of particles the computation time is similar to using directional fingerprinting or Markov localization. But, using step detection did not improve the results in this case. On the one hand, step detection can improve the particle sampling. On the other hand, we had to use a large standard deviation while sampling with the step lengths to prevent the particle filter from getting lost for a period of time until starting to track the pose again. Nevertheless, the presented SIR particle filter is a simple standard particle filter and there is space for

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improvements. Using the presented particle filter 80% of the positioning errors are less than 3 m and 80% of the azimuth estimation errors are less than 20°. Directional fingerprinting and Markov localization performed only slightly worse. In summary, the estimation results demonstrate that all of the presented algorithms can be used for pose estimation.

V. CONCLUSIONS

In this work different algorithms for estimating position and azimuth of a pedestrian using directional Wi-Fi RSS measurements are presented and evaluated with measurement data. The algorithms include directional fingerprinting, Markov localization and particle filtering. Instead of collecting RSS measurements with a bar antenna a set-up of four directional antennas is used. With the help of Wi-Fi signal propagation models it has been demonstrated that a mean directional signal strength vector measured in an area with a directional antenna and a constant heading is characteristic for that area. Therefore, directional signal strength measurements can be used for pose estimation using fingerprinting. Pedestrian dead reckoning based on the propagation of steps in direction of the azimuth angle has been included in the prediction steps of the tracking algorithms. Measurements collected inside and outside of an office building demonstrate that all of the presented algorithms can be used for pose estimation. The different characteristics of the algorithms are discussed. The proposed SIR particle filter with step detection performed best. 80% of the measurement errors are less than 3 m and less than 20°. Azimuth and position can be estimated continuously. Based on the presented results, this approach for horizontal pose estimation can e.g. be used for electronic guiding systems.

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