Position Estimation Based on MEMS Inertial Sensors for the Use as Pedestrian Navigation

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Key words: Indoor Navigation, MEMS, Position Estimation, Particle Filter, Pedestrian

SUMMARY

The research for pedestrian navigation is still an interesting field. Pedestrian navigation in GNSS-shaded areas helps to close the route of outdoor navigation. There are a lot of possibilities to realize position estimation without GNSS. Different technologies are used, e.g. Wifi, Bluetooth, inertial sensors and cameras. In this paper a classification is used which helps to identify the differences of the main technologies. The technologies for position estimation in buildings can be distinguished into image-based, infrastructure-based and hybrid/autonomous methods. Subsequently, a favoured inertial-based position estimation is presented. This approach is based on particle filter and uses a routing graph and map of the test building to correct the pedestrian dead reckoning position. The effort of only using inertial sensors results in a low effort in realizing a navigation solution, e.g. as in infrastructure-based applications. Test runs and results made in a controlled test scenario are shown. The differences to reference coordinates are smaller than 5 meters. Additionally, 40 data sets were generated by 20 persons, which had been using the application for the very first time. In these data acquisition nearly 70 % of all data reach the quality of the controlled test scenario. This paper closes with the discussion of the actual results and gives a short outlook.

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1. INTRODUCTION

Navigation in GNSS-shaded areas is interesting for different applications, e.g. pedestrian navigation in shopping malls, airports, areas of public transport and big offices. Moreover, there are a lot of industrial applications which require positioning data to realize automation processes. The research field is strongly interdisciplinary and different strategy fields exist in this working field. Because of numerous different applications, the requirements, too, vary greatly. The pedestrian navigation needs an easy handling for the users and less effort for the implementation. On the other hand industrial approaches often need a better accuracy.

Positioning methods can be classified based on their characteristics like accuracy, costs, areas of use, effort of implementation. In Blankenbach 2016, a classification is presented which is based on the technology used: infrastructure-based, image-based and hybrid methods. In hybrid methods inertial systems with less accuracy are used in combination with infrastructure- or image-based methods.

In this paper, the focus lies on the realization of a position estimation which uses the inertial sensors in smartphones. This technology is normally assigned to hybrid methods, but in this paper the approach works autonomously, without any correction by other methods. This helps to have an easy implementation with less cost. By the use of smartphones, the combination of indoor and outdoor navigation is relatively easy. The classification of position estimation methods in indoor positioning is described in the following chapter 2 in order to get a better understanding of this approach.

2. CLASSIFICATION OF POSITION ESTIMATION METHODS

2.1 Infrastructure-based methods – e.g. Wifi fingerprinting

All positioning methods can be assigned to this field, which is based mainly on technologies in which the infrastructure needs to be changed. It includes technologies based on Wifi, Bluetooth, ultrasound, Ultra Wide Band (UWB) and special approaches of magnetic fields (Blankenbach 2016).

As an example, a realization of the position estimation based on Wifi fingerprinting is presented. Figure 1 shows the working principle of fingerprinting. First of all, reference data has to be collected in the building. In the typical procedure, Wifi data is recorded on known positions (P11 - P19). This data base is the basis for the position estimation. On the left side in figure 1, the positioning method is presented. Actual measurements of Wifi signals are compared to all saved known positions in the reference data base.

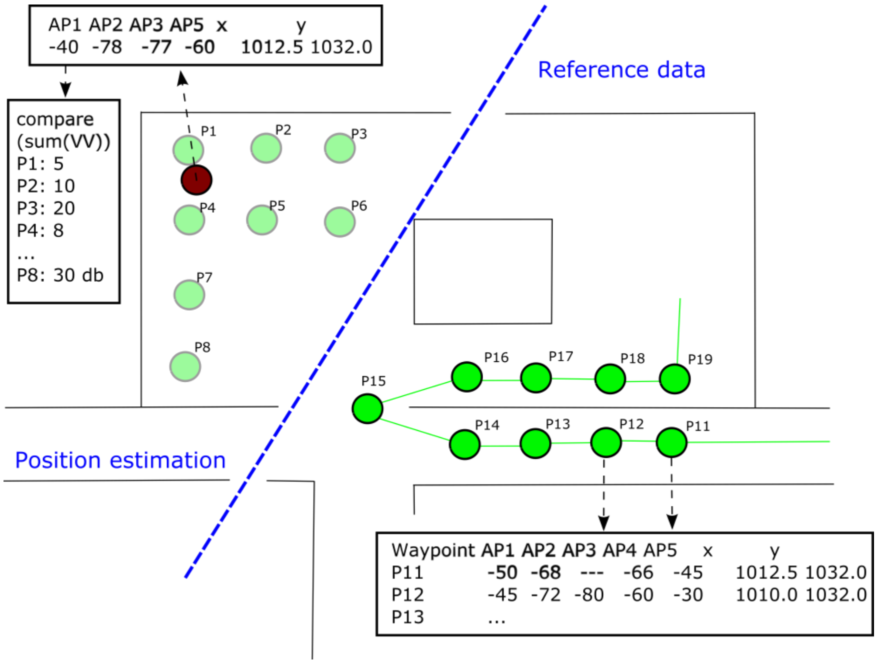

Fig. 1: Principle of Wifi fingerprinting (Willemsen 2014)

The comparison can be implemented in two fundamentally different procedures. The first procedure is shown in figure 2 which uses the Euclidean distance as a deterministic approach. Here, the square sum of differences to the actual measurements is calculated for every position in the reference data base. The minimum square sum is the actual position. Figure 2 shows the square sum of all reference positions in the HafenCity university building.

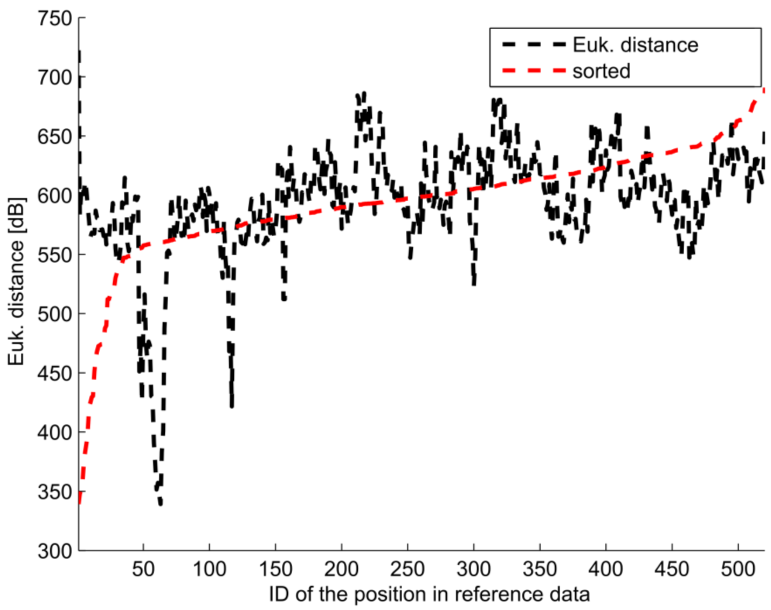

Fig. 2: Position estimation based on Euclidean distance (Willemsen 2016)

The second procedure is the occupancy grid. In this probabilistic approach difference values are divided into areas which are represented with weights / probabilities. The multiplication of all differences of every position is used. After normalization, figure 3 shows the results for one position estimate in the building of the HafenCity University. For the comparison of both position estimation methods, 20 survey points are measured in the building on different floors. The position estimation is based on the same reference data base. The main difference between both position estimations is the use of the measured data. The deterministic approach directly uses the difference values to find the position. The probabilistic approach works with difference areas which helps minimize noise effects of receiving data. Table 1 presents the results of the deterministic (Euclidean distance) and the probabilistic (occupancy grid) approach. When comparing both approaches, it can be seen that the probabilistic approach in this data set is more robust than the deterministic approach. The fourth floor has many corridors and rooms thus helps to have varies signal damping in the data. On the first floor, the university has big open areas. The result shows clearly that the quality of this infrastructure-based method mainly depends on the room structure of the building. To optimize the position estimation in open areas, a big effort is necessary and more access points have to be built-in.

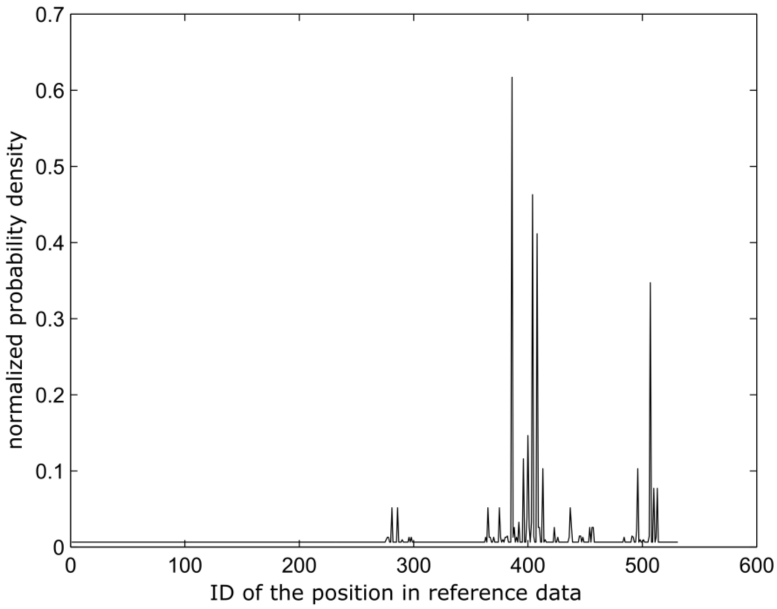

Fig. 3: Position estimation based on normalized probability density (Willemsen 2016)

Tab. 1: Comparison of the position estimate based on Wifi fingerprinting in the test building. Both methods, the deterministic and the probabilistic approach, are used. The value of 0.0 means that the actual position corresponds with the reference position in the reference data base (Willemsen 2016).

Control point	**Euclidean distance [m]**	**Occupancy grid [m]**	**Control point**	**Euclidean distance [m]**	**Occupancy grid [m]**
Data set 4th floor			**Data set 1th floor**		
1	0.0	0.0	1	28.9	42.5
2	3.2	2.9	2	26.5	0.0

3	10.2	0.0	3	3.1	2.7
4	0.0	0.0	4	0.0	0.0
5	3.0	3.0	5	7.9	3.8
6	0.0	0.0	6	24.9	5.0
7	0.0	0.0	7	28.0	8.1
8	2.4	3.3	8	10.8	10.8
9	2.7	3.3	9	3.1	3.1
10	0.0	0.0	10	6.7	0.0

2.2 Hybrid/autonomous methods - MEMS inertial sensors

All position estimation methods based on inertial sensors are called hybrid or autonomous methods. The position estimations produce large position errors over time, due to the integration of residual errors of the sensors. Normally, additional positioning methods are used to correct this position estimation by inertial sensors. If there are additional corrections by infrastructure- or image-based methods, the position estimation is named “hybrid” and if there are no such corrections, it is named “autonomous”.

For pedestrian navigation, the inertial sensors are used in pedestrian dead reckoning (PDR). In this approach, the start position is needed. In equation (1), the PDR function is shown. In the rotation matrix R_z , the orientation/azimutr_z is used (2). In addition, the step length l_{step} (3) is required for determining the scale factor. In some realizations, the step length is estimated out of the step signal seen in the acceleration data.

$$\vec{x} = \vec{x}^{-} + R_z \times t \tag{1}$$

$$R_z = \begin{pmatrix} \cos r_z & \sin r_z \\ -\sin r_z & \cos r_z \end{pmatrix} \tag{2}$$

$$t = \begin{pmatrix} l_{step} \\ 0 \end{pmatrix} \tag{3}$$

An 80 m route, which is walked in 60 seconds, is shown in figure 4. As test device the Samsung Galaxy Nexus (2011) is used. The blue line shows the PDR, computed directly with raw data. It is evident that the position quality decreases over time. The biggest influence is mainly caused by the sensor-inherent noise of inertial sensors. To minimize this influence, offsets are determined and corrected during standstill. This correction is called “Zero Velocity UPdaTe” (ZUPT). The green line shows the trajectory, calculated after using ZUPT. The result reveals that the use of inertial sensors as autonomous method still needs corrections.

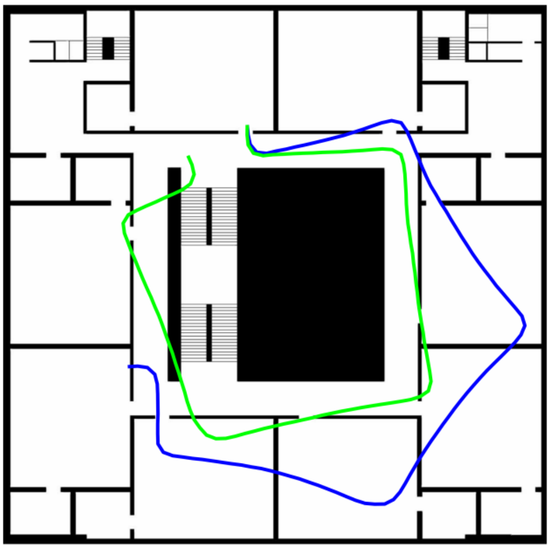

Fig. 4: Pedestrian dead reckoning trajectory in the HCU building. (blue: without correction; green: correction of the orientation with Zero Velocity Update) (Willemsen 2016)

2.3 Image-based methods

In image-based methods, cameras are used to estimate positions and/or orientations of objects. Different approaches exist for this objective. The main difference of these approaches is how the cameras are positioned. The cameras can be installed on the moving object or be fixed in the navigation area.

Willert 2011 and Handler 2012 describe a method using coded marks on doors, to automatically find the doors in pictures. Afterwards, the geometry of the door is used to calculate the actual position with the spatial resection. In this approach, a smartphone camera is applied. In other approaches, features are used to estimate the relative orientation between pairs of pictures, e.g., in Marouane 2015 where the camera is used for step detection.

Due to high requirements in regard to processor power and light conditions, the use of image-based methods is actually not suitable for civil pedestrian navigation.

2.4 Discussion

In this work, the pedestrian navigation is the main application. Currently, a lot of isolated applications exist, as well as a large number of different realizations. To combine the outdoor (GNSS-based) navigation with indoor navigation, an easy approach based on smartphones is needed. In addition, the realization in buildings must be easy and cost-efficient. This supports the social acceptance and makes it easier for companies to realize pedestrian navigation in their buildings.

Based on the before mentioned classification, the three position estimation groups have advantages and also disadvantages. The main advantage of infrastructure-based methods is the robust position estimation. But the position accuracy depends of the building and needs many efforts. The main disadvantage of image-based methods is the dependence of light conditions. The light conditions are only stable in building complexes like airports. Inertial sensors need additional corrections. If the use of inertial sensors in smartphones as hardware is the only possibility, the use in buildings needs no infrastructure changes. The combination with outdoor navigation is quite easy.

Therefore, inertial sensors in smartphones are the favoured technology in this work in order to realize indoor pedestrian navigation. The aim is a positioning method with less work for users and provider.

3. FAVOURED APPROACH

The necessary of correction information to improve the position estimation based on inertial sensors is described previously in this paper. In the following approach, a particle filter based on PDR is developed.. In addition, the particle filter dealt with map data and a routing graph to correct the position in a special way.

3.1 Basics of particle filter

The most relevant distinction in the working principle between particle filter (PF) and Kalman filter (KF) is the processing of probabilities. In KF, the uncertainty can be found in the covariance matrix, in PF, however, the uncertainty is depicted in particle weights.

The basic functional relation is found in equation (4) and (5). The propagation (4) rests on a functional model which is built out of all known information about the expected behavior. The system noise w_k is necessary in order to describe the uncertainty of the functional model.

$$x = f(x_{k-1}) + w_k \tag{4}$$

The PF works with a defined number of particles which represent all possible positions. In the propagation step, all particles are estimated based on the step before. Each particle has its own weight. The weight varies by using the measurements.

$$y = h(x_k) + v_k \tag{5}$$

The correction (5) includes the functional relation between measurement *y* and the state vector *x*. In the correction step, all particle weights receive their new weight by comparing the current particle value with the measurements.

The last step in the particle filter is the resampling. Figure 5 shows the working principle. After some iteration, fewer particles include all weights. This leads to an instable PF. In the resampling step, the remaining particles were reproduced by using the curent particle weight. At top in figure 5, all particles have the same weight *1/n*. After the correction step, the particles get new weights. The range between 0 and 1 is used for all particles in the resampling. With the use of randomized numbers between 0-1 n, particles are produced. Particles with big weights are reproduced more often than particles with small weights.

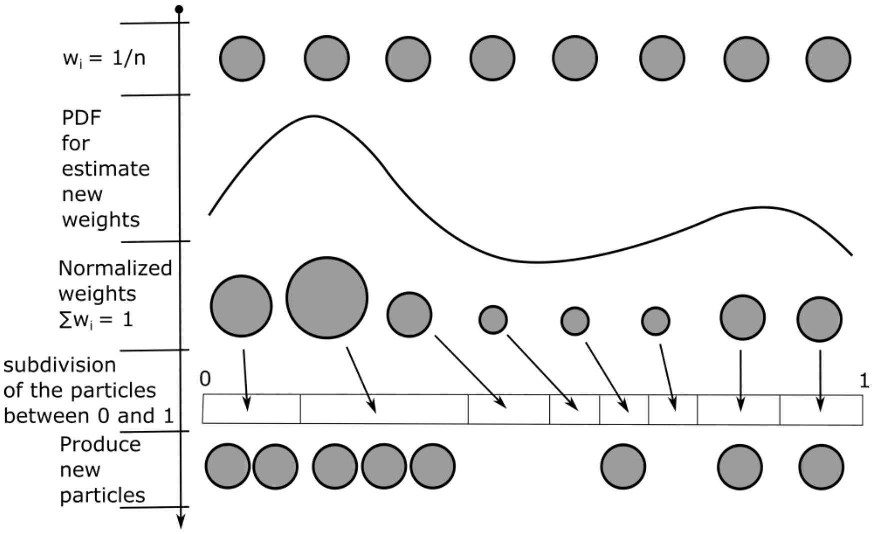

Fig. 5: Resampling principle in bootstrap particle filter (based on Aggarwal 2010 and Wendel 2011)

The value N_{eff} (6) is calculated in order to find out the necessity to resample in the actual iteration. This value indicates whether some few particles have the major part of the weight.

$$N_{eff} = \frac{1}{\sum_{i=1}^{N}(w^i)^2} \tag{6}$$

One option to combine PDR, map data and routing data in a PF is shown here. The particle includes the 2D position (7). In equation (8), the propagation step is presented as a PDR. Orientation and the step length get their own uncertainty ε for every particle *i*.

$$\vec{p}_i = \begin{pmatrix} x_i \\ y_i \end{pmatrix} \tag{7}$$

$$\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \begin{pmatrix} x_i^- \\ y_i^- \end{pmatrix} + \begin{pmatrix} \cos(r_z + \varepsilon_{r_i}) & \sin(r_z + \varepsilon_{r_i}) \\ -\sin(r_z + \varepsilon_{r_i}) & \cos(r_z + \varepsilon_{r_i}) \end{pmatrix} \times \begin{pmatrix} t_{step} + \varepsilon_{t_i} \\ 0 \end{pmatrix} \tag{8}$$

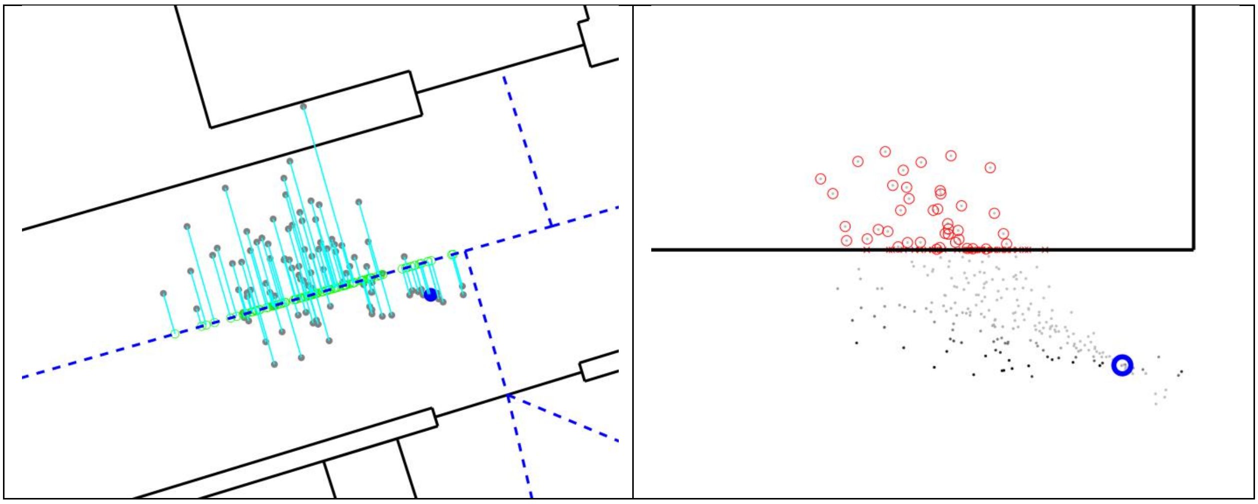

Fig. 6: Correction with routing edges (left) and walls (right) in the particle filter (Willemsen 2015).

In the correction step, the routing data and the map data are used to find new weights for every estimated particle. Figure 6 shows on the left side a calculation of orthogonal offsets from all particles to the favoured routing edge. With the orthogonal offset $d_{ortho,}$ the particle weights w are calculated (9). On the right side in figure 6 the particle weights are calculated in dependence of the wall orientation (gray scaled). Equation (10) shows the respective function. In addition, all particles behind the wall (red particles) obtain the weight 0. The measurement noise, presented in the matrix R, allows control of the correction efficiency.

$$w_i \ = exp[-0.5 \times (d_{ortho}) \times R_{ortho}^{-1} \times (d_{ortho})] \tag{9}$$

$$w_i = exp\left[-0.5 \times (r_i - r_{wand_j}) \times R_r^{-1} \times (r_i - r_{wand_j})\right] \tag{10}$$

3.2 Edge-based PDR particle filter

In chapter 3.1 “basics of particle filter”, the working principle and two examples were presented including map data and routing graph. The including of routing graph in the position estimate is the big challenge. In buildings the routing doesn’t represent the typical walking ways of persons. A correction by routing edge could produce additional errors in the position estimate. So in this chapter, a particle filter is introduced which works mainly on the routing graph and reduces with different states the increasing of position uncertainly. The working principle is shown in figure 7. On the right side, the gray colored point presents the initial position, for example by using a QRcode on doors. The next routing edge is determined and the particle filter is connected to the routing graph.

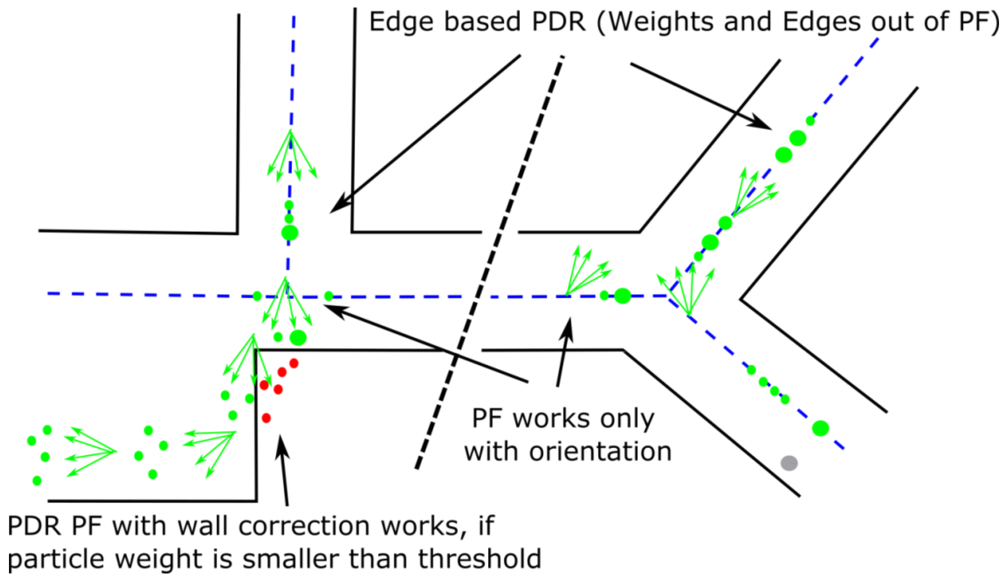

Fig. 7: Working principle of the favoured particle filter approach (Willemsen 2016).

The particle vector includes the 2D orientation *r*, the particle weight *w* for orientation, the position (*x*, *y*, *z*) and the identification number ID_{edge} of the actual routing edge (11). The change of weights is based on differences to routing edges around the actual estimated position (12).

$$\vec{p}_i = \begin{pmatrix} r_i \\ w_i \\ x_i \\ y_i \\ z_i \\ ID_{edge} \end{pmatrix} \tag{11}$$

$$w_i = exp\left[-0.5 \times \left(r_i - r_{edge_j}\right) \times R_r^{-1} \times (r_i - r_{edge_j})\right] \tag{12}$$

Figure 9 illustrates the workflow. The PF works as a state detection on the routing graph. The states which are included in this workflow are shown in figure 8. They deal with the orientation difference between actual orientation and edge orientation. They describe different position and orientation situations on the routing graph. The aim is to find the best possible routing edge for the position estimate. This minimizes the influence by drift errors. The basic approach of state detection on the routing graph without using filter algorithm is presented in Willemsen 2015.

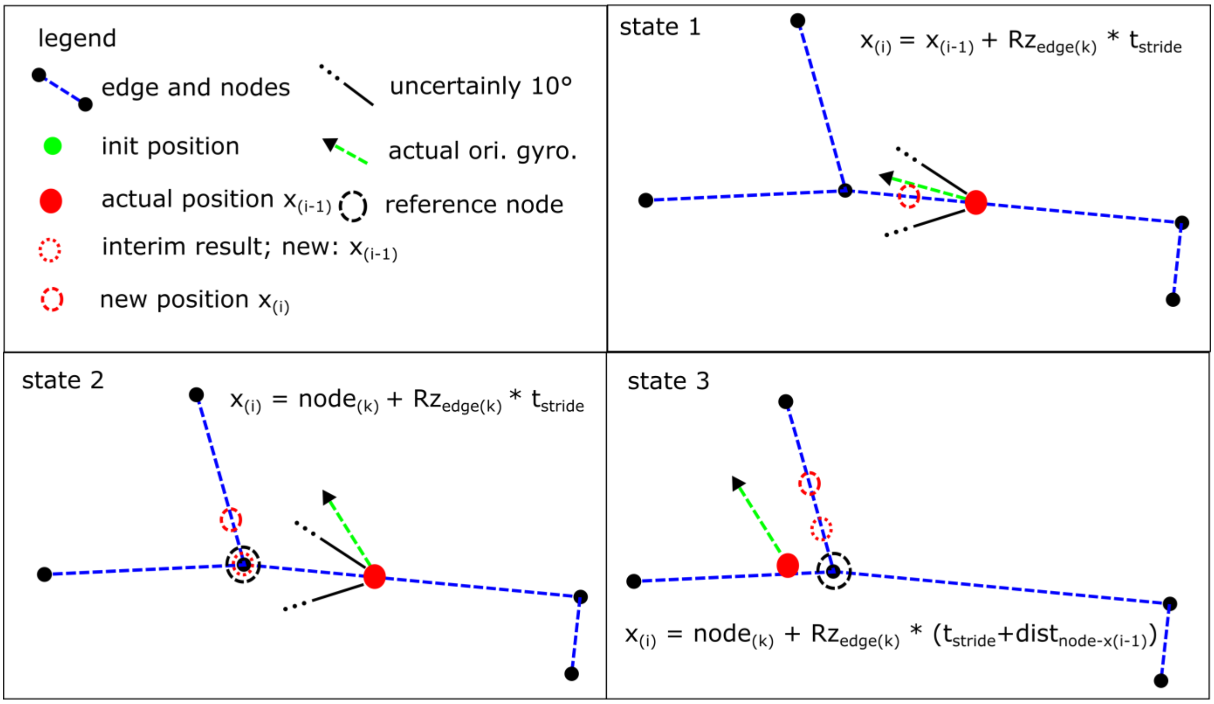

Fig. 8: States for the position estimate based on inertial sensors in the PF (Willemsen 2015).

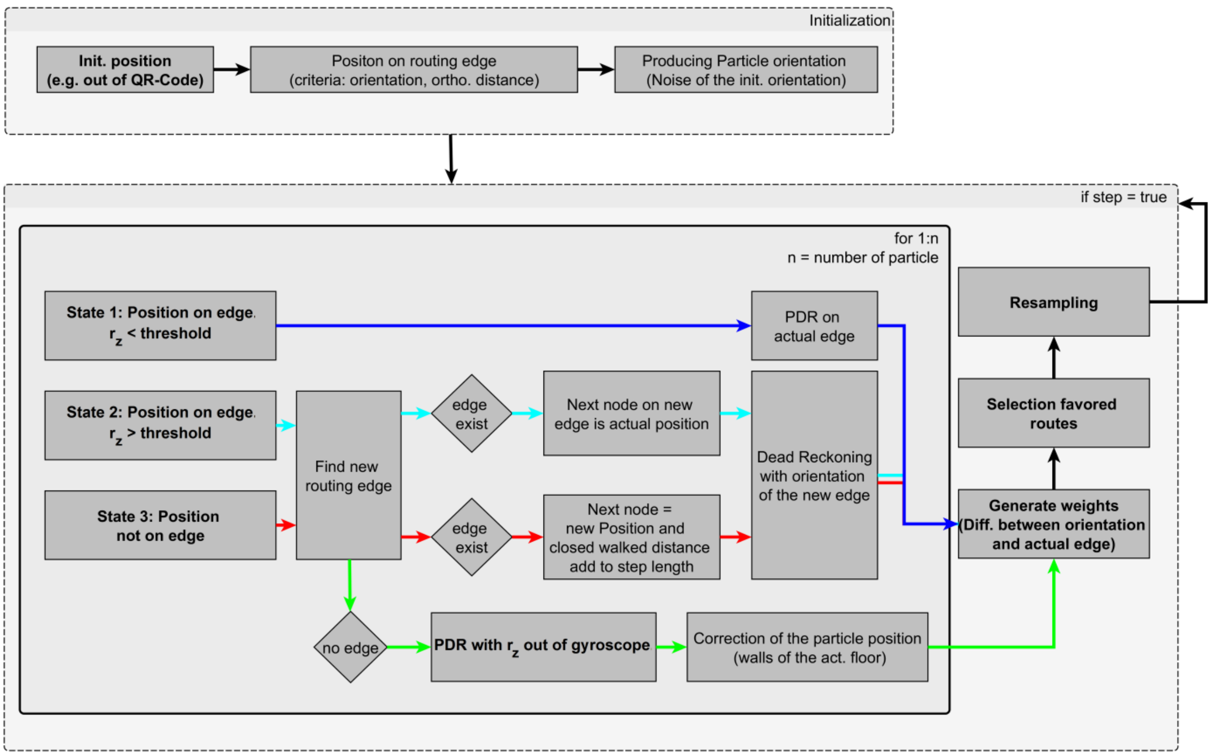

Fig. 9: Workflow of the edge-based particle filter (Willemsen 2016).

The selection of the routing edge for every particle is based on the orientation difference. The position estimation is then adopted from the state for every particle. If there is no routing edge close to the actual particle position and the particle orientation is available, then the filter allows an uncoupling from the routing graph. This particle works as a PDR PF with correction by map data, see figure 7.

3.3 Results

3.3.1 Optimal test scenario

The presented particle filter approach is realized with matlab and tested with real smartphone data. For that, an android-based application was developed to store all necessary sensor data with time stamp. The test device was Google Nexus 4 and a number of particles were set to 100. In this first result, an optimal test scenario was simulated. The test person was familiar working with smartphone data and knows how to optimize the sensor data during walking. This includes for example important points as the fixed orientation to the user and clear steps.

All trajectories are compared with uncorrected positions from PDR. Figure 10 shows the trajectories on the upper fourth floor of the HafenCity University. In red, the PDR trajectory is shown. The trajectory starts and ends at the blue point. It is obvious that the quality of the PDR decreases fast. In magenta, the edge-based PF is shown. The selection of the favoured route results from a weighted mean value of the particle collection that has the largest number of particles for a routing edge.

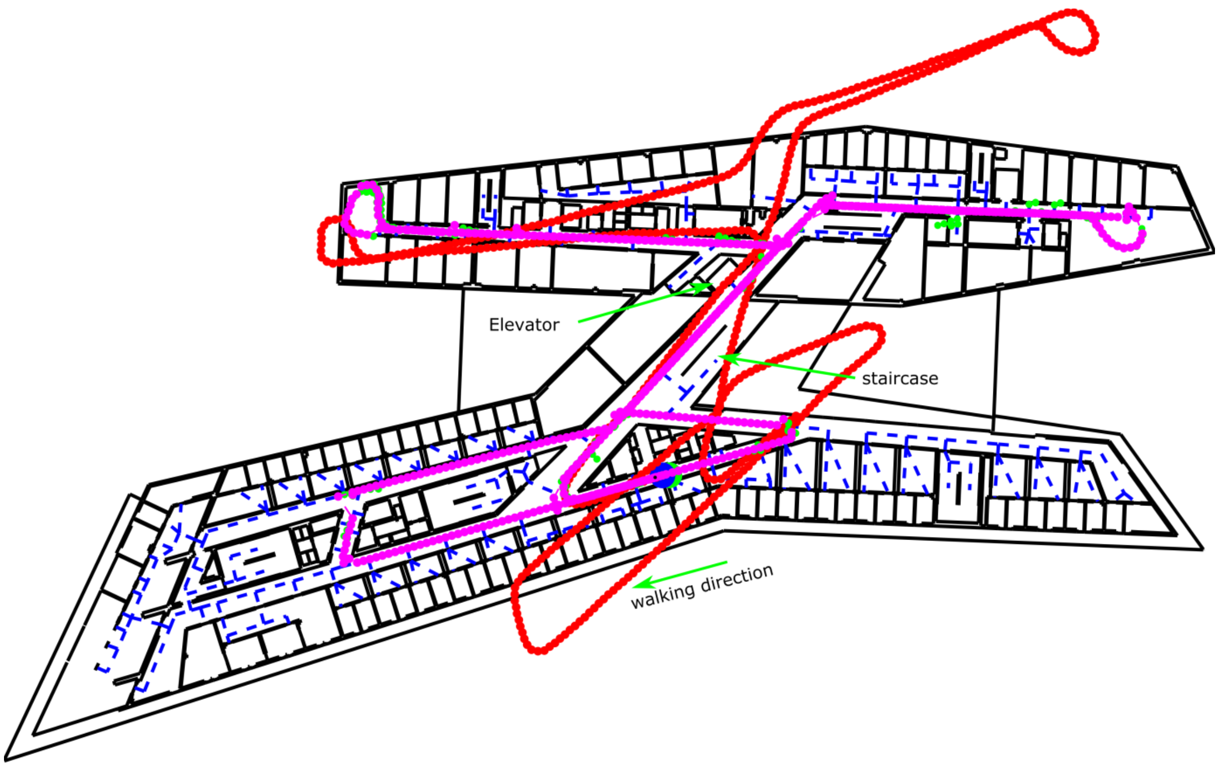

Fig. 10: Trajectories on the fourth floor of the HafenCity University (red: PDR, magenta: edge-based PF) (Willemsen 2016)

Furthermore, the trajectory represents the reference trajectory with a maximum difference of 5 m. It works perfectly in areas where routing edges are present and also in open areas, as shown in figure 10 at top left and right side. For a better understanding of the working principle, figure 11 exposes details of the trajectory which is shown in figure 10. One major advantage of this approach is the uncoupling and back coupling of the particle position on the routing edges. The individual particles are plotted in green. If there are no corrections, the uncertainty increases and the particles spread (left side). On the right side, an uncoupling and a back coupling of the main trajectory (magenta) is shown.

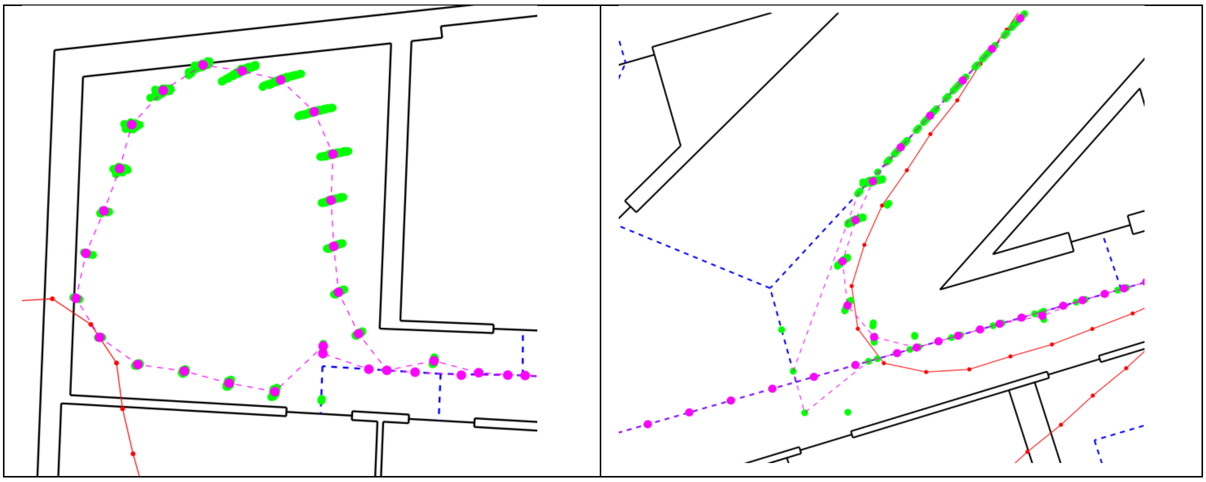

Fig. 11: Details of the trajectory shown in figure 10 (Willemsen 2016).

3.3.2 Sample of users

20 test persons have generated test data in order to get representative results on the social applicability. These 20 test data sets were made by 16 men and 4 women with 7 different smartphones, e.g. Samsung S3, Sony Z3. Most of the test data were generated with Samsung Galaxy Nexus and Google Nexus 4.

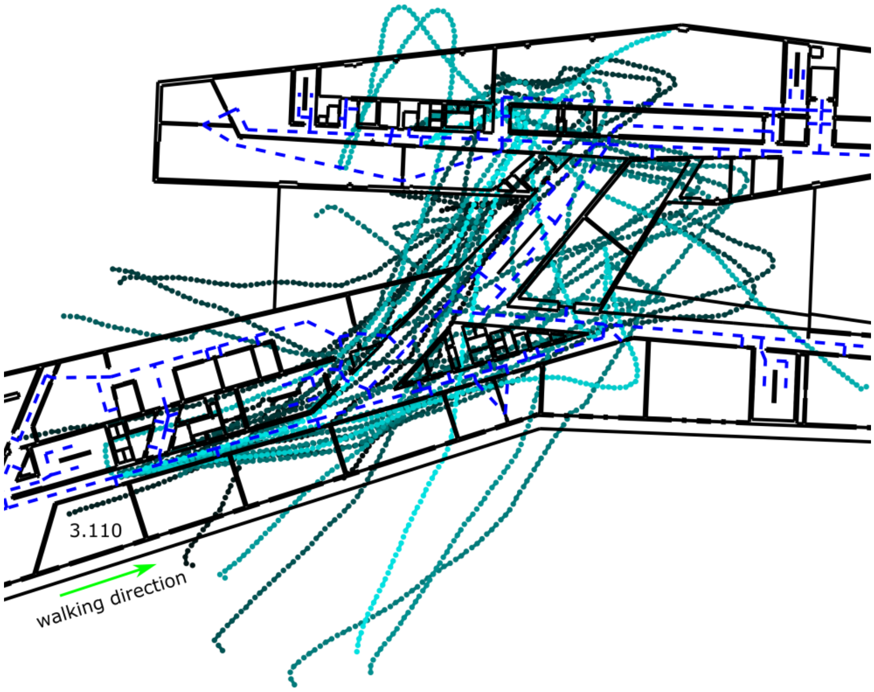

Fig. 12: Position estimation of the test data based on PDR without correction information (Willemsen 2016).

Figure 12 shows all 20 trajectories based on PDR of the test data sets. Start and end position were set for the users at room 3.110. An intermediate stop was set on the north side of the building. The position estimation is based on raw data without any correction by map data or routing graph. It is obvious that the position estimation with this uncorrected data cannot be used for indoor navigation. These raw data were put into the edge-based particle filter. The results are shown in figure 13. In comparison to the results in figure 12, the walked trajectory is now clearly visible. Only the minority of the routes move away from the real walk. In table 2, a comparison of all 20 trajectories with the two position estimations is presented. For this comparison the magnitude of the coordinate difference to the reference end point is calculated.

Tab. 2: Comparison of the test data based on the difference to reference points (GN = Samsung Galaxy Nexus, N4 = Google Nexus 4) (Willemsen 2016).

Diff.	**Algorithm**		**Gender**		**Smartphone model**		
	Edge-based PF	PDR	w. (4)	m. (16)	Other (6)	GN (8)	N4 (5)
0-5 m	14	0	2	12	5	4	5
5-10 m	2	2	1	1	0	2	0
+10 m	4	18	1	3	1	2	1

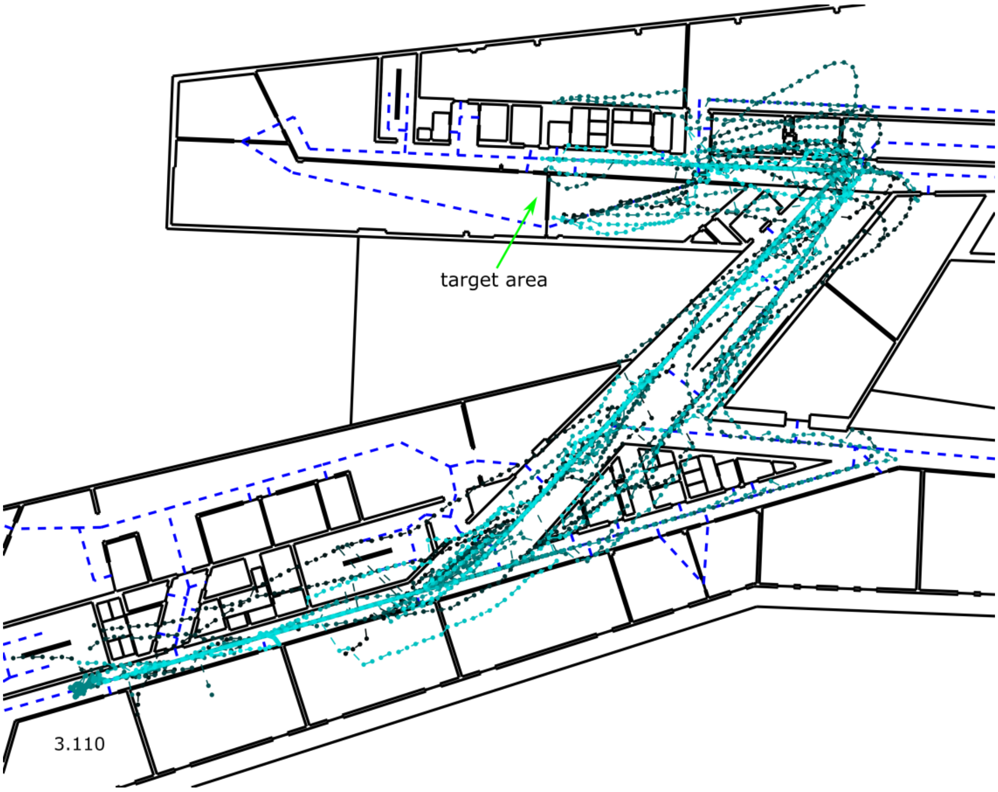

Fig. 13: Position estimation based on edge-based particle filter (Willemsen 2016).

Table 2 shows the differences between the algorithms (edge-based PF and PDR), gender and smartphone models. Because of the low number of test data, these illustrated differences are only usable as small indications. The coordinate difference was categorized in three areas. In this work, a position quality less than 5 m is good enough for the use in navigation applications. 70 % of the 20 test runs got results in this quality. Compared with PDR, it is evident that the algorithm allows now the use of inertial sensors as an autonomous system. But the results of the other 6 data sets which not reached a quality of less than 5 m show that additional work on the algorithm is necessary. The results, categorized into gender and smartphone model, permit no conclusions. But the difference between Samsung Galaxy Nexus (GN, 2011) and Google Nexus 4 (N4, 2012) allows the discussion about the growing sensor technology over time.

4. CONCLUSION

In this work a small overview about indoor navigation technologies was given. The favoured classification was made into infrastructure-based, image-based and hybrid methods. After that, an actual approach was presented which allows the use of inertial sensors as an autonomous method. This approach reduced the influence by using routing graphs in position estimate which didn't represent the typical walking ways of the users. The standalone PDR was not accurate enough for indoor navigation solutions. The navigation with PDR is possible in combination with map data and routing graph included in a particle filter. Map data and routing graph are necessary information for pedestrian indoor navigation. The map data were used for orientation and visualization. The routing graph was required for the routing during navigation. The presented approach provided for 70% of the test data the envisaged position accuracy. In the future, the quality of sensor data is going to increase with new sensor technologies. Perhaps the results of this algorithm become better by using the latest smartphones. Furhter steps for improving the quality of the position estimation is the specification of the required parameter in the PF by getting more information about the users.

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BIOGRAPHICAL NOTES

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