Using the Magnetic Field for Indoor Localisation on a Mobile Phone

Andreas Bilke and Jürgen Sieck

Abstract Many people have difficulties getting their bearings when entering an unknown building. However, this problem can be solved by localisation and navigation on a mobile phone. This chapter presents a locating system which is based on recognising geomagnetic field disturbances and ambient light. A particle filter is applied to the locating problem. It is used to fuse together the data of both sensors and track the mobile phone. The prototypic implementation of locating takes place on an Android tablet. Different aspects of the particle filter are evaluated regarding their influence on the accuracy of locating. The tests took place in an office building. In the course of these tests an arithmetic mean locating error of 4 m was achieved.

Keywords Indoor localisation · Particle filter · Magnetic field · Ambient light

1 Introduction

A precondition of indoor navigation and localisation is the provision of various applications. Finding an office room in an unknown building is one of these. Most of the common techniques for outdoor localisation, like GPS, are not accessible in buildings. Walls and other obstacles shield the signal and therefore it is not

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possible to receive it indoors (Eissfeller et al. 2005). It is therefore necessary to provide other reliable approaches. Most of the state-of-the-art technologies are either too elaborate or of relatively low accuracy.

Many systems use Wi-Fi for localisation. One disadvantage of this approach is that the signal propagation in the 2.4 GHz band cannot be fully predicted. Magnetic fields, which are distorted in buildings, can, however, be used in fingerprinting techniques such as Wi-Fi.

In this chapter, an infrastructureless localisation system using magnetic field and light intensity fingerprints is described. The accuracy of this system is improved by using a particle filter.

1.1 Localisation Systems

Most of the localisation systems can be divided into the following methods (Hightower and Borriello 2001):

ToA/TDoA The methods of time of arrival and time difference of arrival use signal runtime between sender and multiple receivers. Knowing the runtime and the propagation speed, it is possible to calculate the distance between all nodes. Because of the fixed position of the receivers, the exact position of the sender can be determined using multilateration. Both methods need synchronised clocks to work properly. Special hardware is required, which cannot be used in the scenario described above.

AoA The angle of arrival method uses the angle of incidence at the receiver. Multiple receivers permit calculation of the site. This method also needs complex hardware like antenna arrays or movable antennas.

RSSI The received signal strength indicator uses the characteristic signal attenuation function of a specific technology to determine the current location of a node.

Fingerprint In addition to the direct calculation of distances between nodes, it is also possible to use a statistical approach for localisation. The fingerprint method consists of two phases. In the off-line phase, characteristic signals, such as Wi-Fi signal strength, are measured and stored in a data base together with the location of their appearance. Later, in the on-line phase, these signals are measured again. The pattern is searched for in all previously recorded data base entries. The best matching entry is then used as the location of the mobile system.

Looking at the literature, most systems for localising objects are RSSI or fingerprint based. These theoretical approaches can be applied to different technologies. A Wi-Fi infrastructure is already available in many office buildings, therefore it is often used for localisation since no additional infrastructure is needed. Using a Wi-Fi RSSI system, it is possible to reach a median accuracy of 4.3 m (Bahl and Padmanabhan 2000). One disadvantage of this system is the foreseeability of the signal damping. Damping through walls or water affect the signal propagation and therefore the accuracy. The fingerprint approach does not need such a model and can achieve a better accuracy. However, the fingerprint approach is affected by environmental changes in buildings. If, for example, a piece of furniture is moved in a room, the signal characteristics change. Therefore the fingerprint data base has to be regularly updated.

The possibility of using magnetic field for localisation has been examined in different chapters. There are two different approaches. One of them creates an artificial field. A magnetic field sensor can detect the direction of the sender. This approach is similar to the AoA method. Since then, this approach has only been tested on small areas. However, the costs of this are high (Blankenbach et al. 2011).

The second approach utilises the earth's magnetic field. One example is a compass to locate mobile robots. The compass is used to estimate the robots' direction. However, the geomagnetic field is distorted in buildings because of steel girders or other obstructions. This leads to an adulterated measurement and, in addition, to a localisation error. This effect is described by Haverinen and Kemppainen (2009) and Storms et al. (2010); a fingerprint map of the specific magnetic disturbance being collected. However, this approach was only tested in a corridor and not on a complete floor.

1.2 Scope of the Work

In this chapter, we describe how the magnetic field fingerprint approach can be applied to larger areas such as floors in an office building. The increasing distribution of smart phones with numerous sensors allows them to be used for indoor localisation.

This chapter also examines whether the light-intensity sensor in mobile phones can also be used. Using the light has the disadvantage of irregularity. It varies in the course of the day or due to changes in the weather. To examine the general possibility of localising with such a sensor, the light situation in the following experiments are regarded as static. Static light situations occur, for example, in museums; therefore it is worth the attempt to investigate this issue.

To improve accuracy, a filter is applied to the system. The Kalman filter is often used, but because of the corresponding light sensor, it is not possible to apply it in this scenario. The predicted system-state of a Kalman filter has to be one position together with a Gaussian-distributed measurement mistake. Using light sources, it is not possible to apply it with this restriction. It is normal that a system-state using this sensor is not unique. However, this happens, for example, on a long facade of windows. As all the places on this facade have the same light intensity, a unique location cannot be determined. In contrast, a particle filter is able to handle such states. Therefore a particle filter is applied to this localisation problem.

Literature provides different extensions to the particle filter. One extension uses a map of the building to suppress invalid particle movements (Wang et al. 2007b). Different extensions are evaluated concerning their influence on the accuracy of localisation.

2 Particle Filter

The particle filter, initially developed by Gordon et al. (1993), is a recursive bayes filter for estimating a system-state using measurements. If the filter is applied to a localisation problem, the system-state is a position in space. The actual position cannot be determined exactly in most cases. The goal of the filter is to contribute a probability density function which describes the position of a device. This function is represented by particles. They consist of a state and a nonnegative weight. A high weight means it contributes more to the function and hence more to the estimated position. The set of particles is defined by:

$$\chi = \{\langle x_i, w_i \rangle \mid i = 1, \ldots, N\}$$

In which x_i is the state of a particle and w_i the corresponding weight.

The filter consists of two essential steps. In the motion model, the particles discover the state space using a transition function and, in the measurement model, the particle positions are evaluated and new weights are assigned on the basis of the measurements.

2.1 Motion Model

During the motion model, all particles discover the state space. The transition between states is described by means of a mathematical model. It is also possible to use inertial sensors for this model (Wang et al. 2007a). Using inertial sensors, a step and direction detection can be realised. Within these parameters, the particles can be moved through the state space.

This chapter uses a Gaussian randomised model (Bruce and Gordon 2004; Widyawan 2010). The motion parameters are extracted from random numbers.

The new speed of a particle is described with:

$$v_t \Big| = \mathcal{N}(v_{t-1}, \sigma_v), \; v_t = \begin{cases} v_t, & 0 \le v_t \le Max_{v_t} \\ |v_t|, & v_t \le 0 \\ Max_{v_t}, & v_t > Max_{v_t} \end{cases}$$
$$\sigma_v = \min(Max_{\Delta t})$$

The expected value is the speed of the last particle step. The standard deviation is the time difference between the occurrence of two measurements. An increasing time difference leads to an increasing probability of changing the speed in contrast to the last one. Variable Max_{v_t} describes the maximum speed of a particle. It is set to 10 ms^{-1}, since this is approximately the maximum speed a human being can walk (Widyawan 2010). $Max_{\Delta t}$ is the maximum time difference between measurements. It is set to 3 s.

The direction of a particle is based on its speed. The assumption is that a direction change is less probable if the speed is high and vice versa. If a person moves around a corner, one's speed is mostly slow. The following formula describes this process:

$$\alpha_t = \mathcal{N}(\alpha_{t-1}, \sigma_\alpha)$$

$$\sigma_\alpha = 0.4\pi - \arctan\left(\frac{\sqrt{v_{t-1}}}{2}\right)$$

Both variables are afterwards used to move the particle:

$$x_{i,t} = \begin{pmatrix} p^x_{i,t} \\ p^y_{i,t} \end{pmatrix} = \begin{pmatrix} p^x_{i,t-1} + v_{i,t}\cos(\alpha_{i,t})\Delta t \\ p^y_{i,t-1} + v_{i,t}\sin(\alpha_{i,t})\Delta t \end{pmatrix}$$

2.2 Measurement Model

The measurement model is used to evaluate the particle state. In this step, the particle weight is updated on the basis of the new measurements. The particle state always corresponds to a fingerprint position since a fingerprint approach is used. For each particle the nearest fingerprint will be searched for. Afterwards, the measured-data vector is compared to the data stored from the fingerprint. The comparison of both vectors is realised through a similarity function. This chapter evaluates three similarity functions regarding their impact on the accuracy. These functions are the Gaussian distance, cosine similarity and a probability-based function.

The vector measured corresponds to a point in the measurement space. The Euclidean distance describes the direct connection between both points. It is defined through:

$$d(\bar{x}, \bar{y}) = \|\bar{x} - \bar{y}\| = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$

The cosine similarity, often used in the field of information retrieval, calculates the angle between both vectors. The measured magnetic-field vector points to the earth's magnetic north pole. The direction is distorted in buildings. In this case, the cosine similarity may be used to recognise the specific refraction. It is defined by:

$$d(\bar{x}, \bar{y}) = \frac{\bar{x} \cdot \bar{y}}{\|\bar{x}\|\|\bar{y}\|}$$

The probability approach, based on a Gaussian function, is able to consider measurement noise. To use this function, the measurement noise has to be determined in advance for the relevant sensor device. Later on, it will be used as the standard deviation parameter in the following function:

$$d(\bar{x}, \bar{y}) = \prod_{i=1}^{N} \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{(x_i - y_i)^2}{2\sigma^2}\right)$$

Using the Gaussian function, a particle weight, w_i can directly be derived. For each dimension of the measured vector, the previously-described function is applied. The total weight is the product sum of all dimensions. With the other similarity functions, only a similarity order can be computed. With the formula:

$$P(z_t|x_t) = 0.5^{i_t}$$

a probability can be constructed from the ordered set. i_t is the position of the fingerprint in the ordered list after applying the similarity function to all fingerprint values.

The magnetic field, measured on the mobile device, is always related to the device coordinate system. In the operating phase it is not possible to ensure a consistent alignment of the device. The measured vector must be transformed into a world-coordinate system. The Android operating system, which is used on the test device, can transform the locally-adjusted vector into a global-coordinate system. Unfortunately, the transformation occurs through the magnetic-field sensor. This leads to an error because of the distorted magnetic field. In a test scenario, it was discovered that, despite the transformation, the vector varies if the sensor is turned in different directions. To overcome this problem, the magnetic field was stored for each direction per fingerprint within the off-line phase. Later, during the on-line phase, the direction was determined again and only the correct data-vector for the corresponding direction was used to compare all fingerprints.

Another enhancement of the measurement model was introduced in by Evennou and Marx (2006). Map data can be used, if available, to control the particle movement. If a particle is moved through a wall during this phase, its weight can be set to zero. This additional step can be described with:

$$w_{i,t} = \begin{cases} 0, & wallcrossed \\ P(z_t|x_{i,t}), & otherwise \end{cases}$$

2.3 Resampling

The first versions of the particle filter have one common problem. If the filter evolves through multiple iterations, it is unavoidable that the particle set degenerates. Some particles gets a very high weight while the rest contribute almost nothing to the probability density function. To overcome this, an additional resampling step was introduced (Ristic et al. 2004). The dominant particles are split into several particles with low weights, and the particles with the lowest weight were removed from the set. There are different resampling algorithms; however, in this chapter, the algorithm from Widyawan (2010) was implemented.

2.4 State Prediction

The state of a particle is related to a position of a fingerprint. To compute the estimated system-state, the most probable fingerprint has to be determined. For each fingerprint, all particles which are near to it have to be detected. The weights of these particles are added together—the estimated position is then the fingerprint with the highest total particle sum.

3 Tests

The previously-described particle filter, based on magnetic field and light intensity fingerprints, was evaluated on its performance regarding localisation accuracy. Therefore, five test runs took place in an office building. The particle filter used had several configuration possibilities which were evaluated according to their impact on the accuracy.

3.1 Environment

The total area of the test floor was 300 m^2 with eight rooms in total. About five fingerprints were recorded in each room. The complete floor, consisted of 52 fingerprints and half of the floor 27. The distance between two fingerprints were approximately 2 m. If a localisation error occured, the minimum error was therefore approximately this distance. During the test runs, an arbitrary route through the rooms was taken. A Motorola Xoom tablet computer was used as a test device.

3.2 Simulation of the Localisation

The reviewed configuration options used: the walls within the measurement model took into consideration the direction, different sensors, the similarity function and the number of particles to approximate the probability density function. In total there were 144 different configurations—it was therefore impossible to make a specific test run for each configuration. Instead, all measurement data was stored in a file for later analysis in the previously-mentioned test run. On some randomly selected points, the real location of the device was also additionally stored. An additional simulation software was written to review the behaviour of the particle filter under different configurations. The stored measurement data was used for this step. At each iteration of the filter, the result was an estimated system-state which was compared to the real position from the test run.

This simulation software makes it possible to obtain a mean error for each configuration. The root mean square error (RMSE) was used to compare the results. On the basis of the mean error, the best configuration of the particle filter was determined for this scenario.

The RMSE is defined by

$$\mathrm{RMSE} = \sqrt{\frac{1}{2}\sum_{i=1}^{N}\|p_i^r - p_i^e\|^2}$$

where N is the number of the recorded real positions. p_i^r is the actual position and p_i^e the estimated position. In the following sections, the different algorithm aspects are evaluated regarding their influence on the system performance.

3.3 Wall Aspect

To compare the different algorithm aspects, box-plots where choosen. Each box, including the atennas, contains all measurement errors of the described simulation. The boxes contain 50 % of the data, the thick line in the middle being the median.

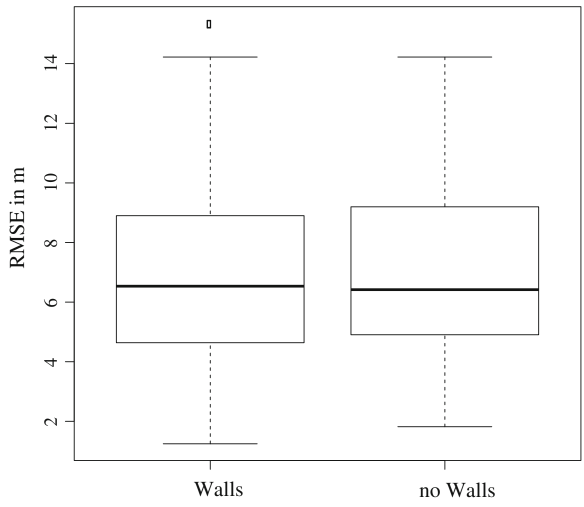
Using the wall aspect, it was determined if map information in the measurement model can suppress invalid particle movements. In Fig. 1, a box-plot is shown which compares the error of all configurations according to the wall aspect. It can be seen that the median of both boxes is very similar (6.53 and 6.41 m).

During the test runs, it was discovered that the filter misjudged the position more often if the wall aspect was used. When the filter recognised the device in an incorrect room, it was more difficult to get the correct position later if wall aspect was used. The particles become devalued if they cross a wall, therefore the filter cannot estimate the correct position when new measurement data arrives—the particles are caught in the room. This algorithm feature is proposed in many chapters to improve the system accuracy. However, while using magnetic fields, it was shown that better results are not achieved with this extension.

3.4 Direction

If the direction was taken into consideration within the measurement model, the median error was 6.43 m; without the observation, it was 6.54 m. At first, better results were assumed by using the direction for selecting the more appropriate fingerprint vector. However, when testing it was concluded that this extension has no measurable effect on the accuracy.

Fig. 1 Error distribution by using the wall aspect in the measurement model



3.5 Vector Similarity Functions

A similarity function has to be used to search for the more similar fingerprint within the data base. Within the test, run three different functions were evaluated. In Fig. 2, the results regarding used function are shown. Using the Euclidean distance, the lowest average error was reached. The Gaussian function, which was assumed to perform better when it comes to noise measurement, leads to the highest error.

3.6 Used Sensors

This chapter evaluates two different sensors for using the fingerprint approach. If only the light intensity sensor was used, an average error of 7.5 m was reached. The magnetic field sensor itself had an error of 6.37 m. If both sensors were combined, the error was 5.93 m (see Fig. 3). Since the used sensors are mostly available in modern mobile devices, they can be used to improve the accuracy without additional hardware.

3.7 Number of Particles

It has been theoreticly proved that an ∞ number of particles approximates the density function best, which leads to the lowest average positioning error (Ristic et al. 2004). However, with an increasing number of particles, the computation

Fig. 2 Error distribution by using different similarity functions

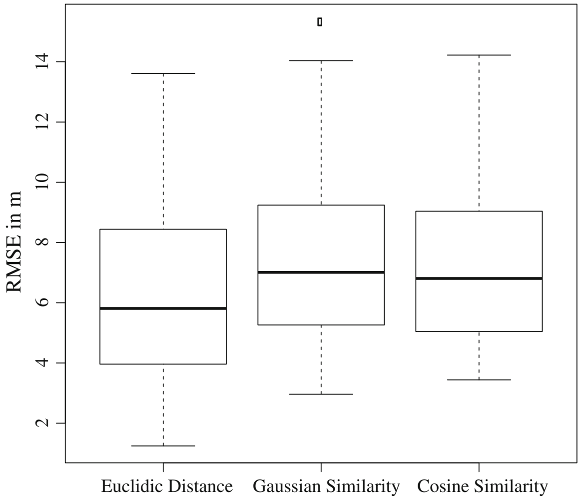
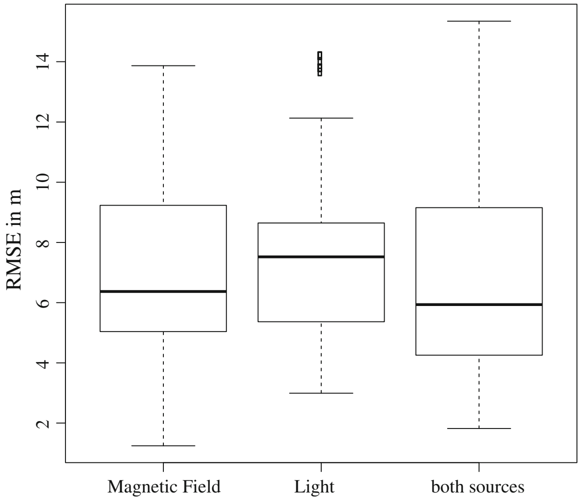


Fig. 3 Error distribution by using different sensors



time for iteration increases as well. A trade-off between error and computation time has to be found. In this chapter. the minimum number of particles which are needed for the scenario is determined.

It was discovered that the minimum number of particles for one floor is about 200. In contrast, other chapters proposed a minimum of 500 particles (Widyawan 2010; Haverinen and Kemppainen 2009). With more particles, the average error was not decreased, so it was not worth investing more computation time on it.

3.8 Best Algorithm Configuration

After comparing different algorithm aspects, it was possible to select the optimal configuration which lead to the lowest error. The configuration did not use the wall aspect, the usage of direction did not matter, the Euclidean distance performed best, the combination of both sensors achieved the best result and only 200 particles were needed to approximate the density function.

Using this configuration, Table 1 was created. The arithmetic mean was 4.1 m. In addition, a cumulative density function could be created (see Fig. 4). This shows the best configuration in comparison to a poor configuration.

The table shows that the average error increases if the used size of the floor also increases. The uniqueness of the fingerprints decreases if more fingerprints in the data set are used. The fingerprint approach using magnetic fields is based on the distorted field within buildings. If the area increases, it might be possible that a typical field disturbance is repeated, which leads to a poorer performance when searching for the best matching fingerprint in the data base.

Beside the total size of the floor, the structure of the individual rooms must be considered. During the tests, it was discovered that small rooms are more suitable for using magnetic field fingerprints. Narrow corridors also show a better performance. This leads to the assumption that steel girders and power cables have, in terms of distance, an influence on the field.

3.9 Comparison to Other Systems

As previously noted, there are several systems for indoor localisation. This section compares other systems with the one in this chapter. Other papers are cited only where the used scenario is comparable to this one.

The different papers are cited in Table 2. There are systems with a Wi-Fi propagation model approach (Bahl and Padmanabhan 2000), fingerprint based systems (Au 2010; Honkavirta et al. 2009; Gansemer et al. 2010; Widyawan 2010), magnetic field based systems (Haverinen and Kemppainen 2009), RFID landmark (Bergemann and Sieck 2011) and also hybrid approaches (Conaire et al. 2008; Evennou and Marx 2006; Chen et al. 2005).

It can be observed that all fingerprint approaches, regardless of their chosen approach, get better results. One disadvantage of the Wi-Fi approach is that it is

Table 1 Statistic value of the localisation error

Test run	RMSE (m)	Median (m)	Arith. mean (m)	Maximum (m)
Compl. floor	8.37	3.72	5.88	22.60
Half floor	3.53	0.00	2.01	14.15
Total result	6.59	1.90	4.09	22.60

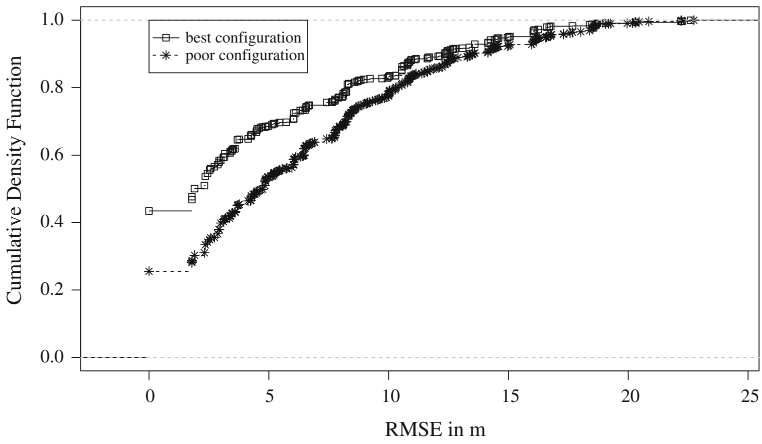


Fig. 4 Cumulative probability for different algorithm configurations

Table 2 Statistic values of the position error in other chapters

Chapter	Type	RMSE (m)	Median (m)	AM (m)
(Bahl and Padmanabhan 2000, p. 783)	WP	–	4.3	–
(Bergemann and Sieck 2011, p. 405)	RF	–	–	2.0
(Au 2010, p. 94)	WF	1.92	–	1.67
(Chen et al. 2005, p. 119)	HB	–	–	2.13
(Honkavirta et al. 2009, p. 250)	WF	5.5	3.8	4.5
(Evennou and Marx 2006, p. 173)	HB	–	–	1.53
(Conaire et al. 2008, p. 4)	HB	–	–	2.00
(Gansemer et al. 2010, p. 5)	WF	–	–	1.80
(Haverinen and Kemppainen 2009, p. 3146)	MF	–	–	3.43
(Widyawan 2010, p. 85)	WF	–	–	1.98

AM is arithmetic mean. Localisation types are WP (Wi-Fi propagation model), WF (Wi-Fi fingerprint), MF (magnetic field), RF (RFID landmark) and HB (hybrids approaches)

not infrastructure-less. It also suffers from signal changes which occur if furniture is moved in rooms or people obstruct the Wi-Fi signal. The magnetic field approach by (Haverinen and Kemppainen 2009) was only tested on a corridor.

4 Conclusion and Further Work

This chapter describes an infrastructure-less indoor-positioning system which uses magnetic field and light intensity fingerprints. The tests took place in an office environment. To improve the accuracy, a particle filter was applied to the system. In a test run, an arithmetic mean error of 4.1 m was reached.

Different extensions of the filter for improving the accuracy were reviewed. Multiple similarity functions for the fingerprint system were evaluated regarding their impact on the accuracy.

In later experiments, it has to be determined if a changing environment (e.g. moved furniture) has an influence on the magnetic fingerprints. Different kinds of rooms should also be investigated concerning their suitability for the described method.

With an increased area, the overall accuracy decreased. Further work on this system can improve it in two different ways.

The decreasing accuracy results from the lack of unique fingerprints. If the area gets bigger, the latter may overlap. One reason is that the sensor used has a noise measurement. In further research, this noise may be reduced by filtering the incoming signals with, e.g. a Kalman-filter.

Another approach may be to use the advantage of the existing magnetic field. This field is mostly distorted in buildings. It is possible to use this without any further installations. Instead of having the fingerprints close together, a combination of fingerprints and inertial sensors may be developed. The movement of a device will then be tracked by inertial sensors, and the estimation of position improved by fingerprints at strategic positions such as doors.

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