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INDOOR NAVIGATION USING PARTICLE FILTER AND SENSOR FUSION

ABSTRACT

In this paper[1] we present an indoor localization system based on particle filter and multiple sensor data like acceleration, angular velocity and compass data. With this approach we tackle the problem of documentation on large building yards during the construction phase. Due to the circumstances of such an environment we cannot rely on any data from GPS, Wi-Fi or RFID. Moreover this work should serve us as a first step towards an all-in-one navigation system for mobile devices. Our experimental results show that we can achieve high accuracy in position estimation.

Keywords:
indor navigation, particle filter, sensor fusion, mobile devices.

INTRODUCTION

Estimating the position of persons in outdoor areas with an accuracy of few meters can mostly be easily achieved by using the Global Positioning System (GPS). However, due to physical restrictions of the GPS signal, using this technique for localization within buildings is not a suitable solution. This is because a steady line of sight to at least four satellites is necessary — a requirement, which is seldom given due to walls and ceilings in the inner of buildings.

Overcoming the indoor-localization problem by using other techniques instead could be a determining factor to make a bunch of new applications possible. One can think about assistance in emergency situations, in which rescue teams are navigated directly to the people, who need their help. Other use cases can be found in more commercial scenarios: A localization application integrated into today's

[1] This work was sponsored by the 'Bayerische Forschungsstiftung'.

smartphones could guide persons through big malls or exhibition centers. Simultaneously vendors could offer advertisement directly in the application and lead their customer to their store or their exhibition stand.

Our work emerged from the problem of documenting the construction phase on big building yards. For this purpose architectural bureaus have to take hundreds and thousands of photos during the development of a building. Every one of these photos afterwards must be manually tagged to the location where the photo was taken, what results in a huge time consuming effort. Therefore we worked on a solution to automatically assign a taken photo to the position it was actually taken, whereat the main problem was to localize the photographer's position with high accuracy.

The circumstances a building yard provides lead to some technological restrictions. Common indoor localization solutions often rely on the use of Wi-Fi or RFID. Since building yards change drastically over time permanent installations of hot spots and RFID-readers become an improper approach. Instead our solution mainly focuses on the use of inertial sensors like accelerometers, gyroscopes and compasses. To overcome noisy sensors we added particle filter, an often used technique to model multimodal uncertainty.

Since the new smartphone and tablet generation have all the mentioned sensors already build-in we see our work as a first step of a project towards indoor localization on mobile devices. The purpose of this paper, therefore, is to show an approach for indoor localization while taking into consideration the above stated constraints.

In the first part an overview of current indoor navigation solutions is given. The second part addresses the theory behind particle filters and how we used this concept to integrate multiple sensor data and map information. Finally experimental results are presented and a short overview is given over our future work.

STATE OF THE ART

Currently, different solutions exist, which tackle the indoor navigation problem. A rough categorization can separate these into absolute and relative localization. The main difference between those two approaches lies in the starting condition. While the relative approach estimates its position based on a fix starting point, absolute positioning on the contrary abstains from it. Absolute positioning approaches also mainly focus on the use of Wi-Fi [6], RFID [7] or Ultrasonic [4]. In these cases position evaluation is done by receiving signals, which are caught by sensors and then processed.

Wi-Fi fingerprinting for example uses essentially two steps to identify the current location. In a first step, the offline phase, a radio map is build, which contains samples of received signal strength (RSS) measurements from different access points. In a second step, the online phase, a signal receiver is used to measure RSS while navigating through the building. The information is gathered in a sample vector and is then compared against the radio map, which allows identifying the current position of a person. Thereby the major drawback of this approach is the training phase. Building up a radio map can end up in a huge amount of time consuming measurements. Furthermore changes of the access points, like removing or adding one, make it necessary to repeat the process of building a radio map. Similar problems occur when relying on data of Ultrasonic or RFID.

Localization solutions with a relative approach rely mostly on measured data from sensors like accelerometers, gyroscopes and magnetometers. On the basis of the initial position every time-step the current position is updated according to the calculated movement.

A commonly known approach in this area is to gather the amount of steps a person has done. Therefore typical patterns in accelerometer and gyroscope data are sought that identify a human movement. During the navigation the actual sensor data is compared against these patterns and the number of steps is multiplied with the pedestrian's step size. Additionally compass data is used to determine the heading.

Using only the three before mentioned sensors, this form of navigation is also found under the term 'Inertial Navigation System (INS)'. Unfortunately a naive implementation of such an approach turns out to not accomplish the indoor navigation problem. Because of noisy sensor readings, integrating acceleration to receive velocity and integrating velocity again to receive the traveled distance sums up to big errors over time.

Statistical approaches have already proved to overcome such uncertainties in other fields of application. In localization, especially in robotics, often particle filter is used, which is a technique to estimate a nonlinear state of a system at a given time and under certain conditions. Song et al. [8] present in their work how they apply particle filter to estimate RSS distribution at each location. Evennou et al. [3] also use the Wi-Fi signal to estimate a position. They integrate this information in the particle filter and add a motion model and map information. Their experimental results show an accuracy of about 1.7 m.

Our approach aims in the similar direction, since we also use a motion model and map information. Instead on Wi-Fi signals, however, our navigation system relies on the use of INS.

SYSTEM DESIGN

General

The problem of estimating the position of a person can be reformulated as the problem of estimating the probability of being in a current state q_t at a given time t, given some observations o_t made at t. Such a calculation corresponds to the a-posteriori probability $p(q_t \mid o_t)$ of a state. For the localization problem it is obvious to define a state as the current position given by its 2D-position $[x, y]$. At every time step t it is necessary to update this state according to some given observations. This can be rewritten as

$$p(q_t|\langle o_t\rangle) = \underbrace{p(o_t|q_t)}_{likelihood} \int \underbrace{p(q_t|q_{t-1})}_{update} \underbrace{p(q_{t-1}|\langle o_{t-1}\rangle)}_{recursion} \, dq_{t-1} \qquad (1)$$

where q_t is the current state at time t and $\langle o_t \rangle$ is a series of observations $o_1, o_2, \ldots, o_t$ [1]. According to (1) this calculation consists of three parts.

The 'likelihood' describes the probability of making an observation while being in a current state. Think about the sensor outputting a position far away from the current position. Since humans underlie physical movement restrictions such information should be associated with a low probability.

In the 'update' the probability of being at a current position under the condition of being at another position at the time step t-1 is formalized. This part is crucial to the navigation process, due to the important information it contains. Since our focus only lies in pedestrian movement, we can assume that a human can only travel a given distance in a given time. For example it is very unlikely to stand 10 meters further ahead in a timespan of only one second. Furthermore obstacles like walls constrain a person's ability of being at some places behind the wall in the next time step. To realize this, we integrate the knowledge of the map into our solution and model the movement speed of a person as a Gaussian distribution.

The third component describes the whole positional information of previous time steps as probability density function in a recursive process. Due to no information at the beginning of the navigation process we assume a uniform probability distribution.

Particle filter

Particle filter is an often used technique for modeling multi-modal distributions [2, 5]. Therefore a set

$$\Upsilon_t = \{\upsilon_t^1 \ldots \upsilon_t^n\} \tag{2}$$

with *N* particles is defined. Each particle υ_t^i consists of a vector

$$\boldsymbol{\chi}_t^i = (x\ y)^T, \tag{3}$$

where *x* stands for the x coordinate and *y* for the y coordinate respectively. Also a weight ω_t^i is added to every particle, which represents how much influence this particular particle has for the overall positioning estimation. The weights ω_t^i are also normalized at every time step so that

$$\sum_{i=0}^{N} \omega^i = 1. \tag{4}$$

In total, a particle hence can therefore be defined as

$$\upsilon_t^i = \{\boldsymbol{\chi}_t^i,\ \omega_t^i\}. \tag{5}$$

With this as bases a particle filter can be rewritten in the following pseudo code:

1. **At time step *t* = *0*:**
   - Initialize *N* particles uniformly over the map with equal weights ω^i.
2. **For every time step *t* do for every particle $\boldsymbol{\upsilon_t^i}$:**
   - Determine a new position $\boldsymbol{\chi}_t^i$ for the particle based on the old position $\boldsymbol{\chi}_{t-1}^i$ using the motion model.
   - Use the given sensor data o_t to evaluate the likelihood of the new position $\boldsymbol{\chi}_t^i$ for this particle.
   - Add υ_t^i to Υ_t.
3. **For *i* = *0* to *N* do:**
   - Draw *n* particles $\propto\ \omega_t^i$ from the particle set Υ_t.
   - Add the drawn particle υ_t^i to Υ_{t+1}.
4. **Repeat 2 to 4 for every time step during navigation.**

As it can be seen every particle represents a belief for the current position. Since at the beginning no information is available the particles are distributed evenly over the map.

Step 2 of the algorithm starts by applying a motion model, randomly moving every particle in a way that could represent a possible pedestrian's movement. Therefore a data structure is calculated offline, which includes all possible movements as probabilities for moving from one point on the map to another in one update step. The floor structure and the human movement speed, which is assumed as Gaussian distributed, serve as basis for this calculation. During the online phase an entry in the data structure is randomly picked at every time step from all possible positions for the next step. This results in a new position with respect to the previously known position. To improve computational speed we also added the possibility to remove points with very low probability from the data structure.

This new position is compared with the position the sensor has observed. The sensor implements therefor an internal INS, which calculates a position from measured sensor data. The probability of the new position is determined from the observed position and a sensor error model. This probability represents the weight of a particle and is accordingly sampled in the next step.

EXPERIMENTAL RESULTS

Figure 1 shows the experimental environment in the 2nd floor at the University of Applied Sciences in Würzburg. The floor map covers an area of about 16m x 30 m. The system was tested with a Intel(R) Core(TM)2 Quad CPU Q9550 @2.83 GHz and 8 GB Ram. The sensor measurements were done with the sensor unit ADIS 16405 by Analog Devices, a triaxal device for each the gyroscope, accelerometer and magnetometer.

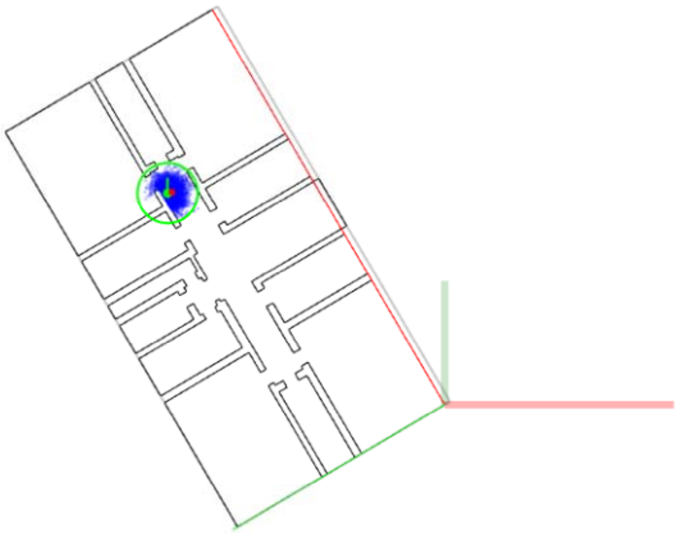

Fig. 1. Experimental Environment at the University of Applied Sciences in Würzburg; the blue dots represent the particles, the green dot the real position and the red dot the estimated position; the green circle shows the growing uncertainty of the sensor data over time [own study]

For testing purposes our system can easily be used with simulated data. Instead of relying on real data from the sensor unit, the sensor was simulated by mouse movement over the map. It is part of nature of INS that over time the estimated position diverges from the real position. We take this fact into account and added a constantly growing variance to the simulated data (see green circle in fig. 1).

Keeping in mind that our long-term goal is to make indoor navigation possible on mobile devices like smartphones and tablets, it is necessary to know how computationally intensive our approach is. Despite the fact that the computational power of smartphones increased with every new generation, it is still not comparable with the computational power of common Desktop PCs. Nevertheless we already achieved a well enough positional estimation with only about 2000 particles (see fig. 2). Testing the maximum performance of our system we had no problems to even manage particle sizes of 100.000 and above, if we rely on an update time of one second (see fig. 3).

Figure 4 shows the positional estimation when using real sensor data. For this purpose the system was tested with a linear walk. After 4 m and 9 m each, we paused for about 6 seconds before we started walking again. The black line shows the idealized walk, the blue line the approximated distance and the red line the approximated distance with additional manual correction. Additional manual correction, like subtracting constant bias, was necessary because the sensor only inadequately realized acceleration both in positive and negative direction, which is the typical effect of the steady sensor drift.

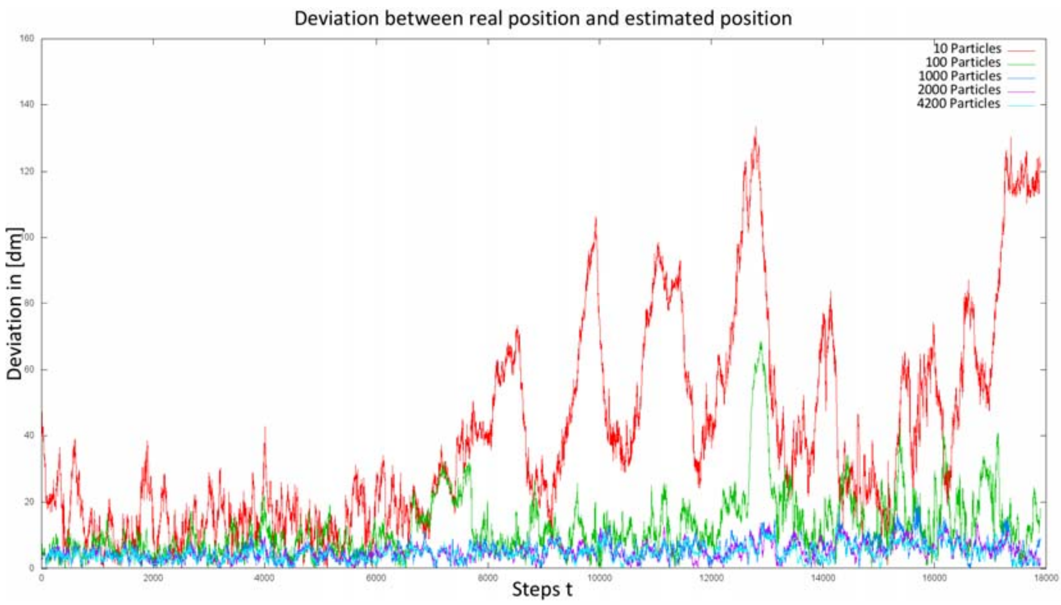

Fig. 2. Depending on the number of particles the difference between the real position and the estimated position is shown; as it can be seen at about 2000 particles the estimation delivers a position estimation, which cannot be outperformed if more particles are added [own study]

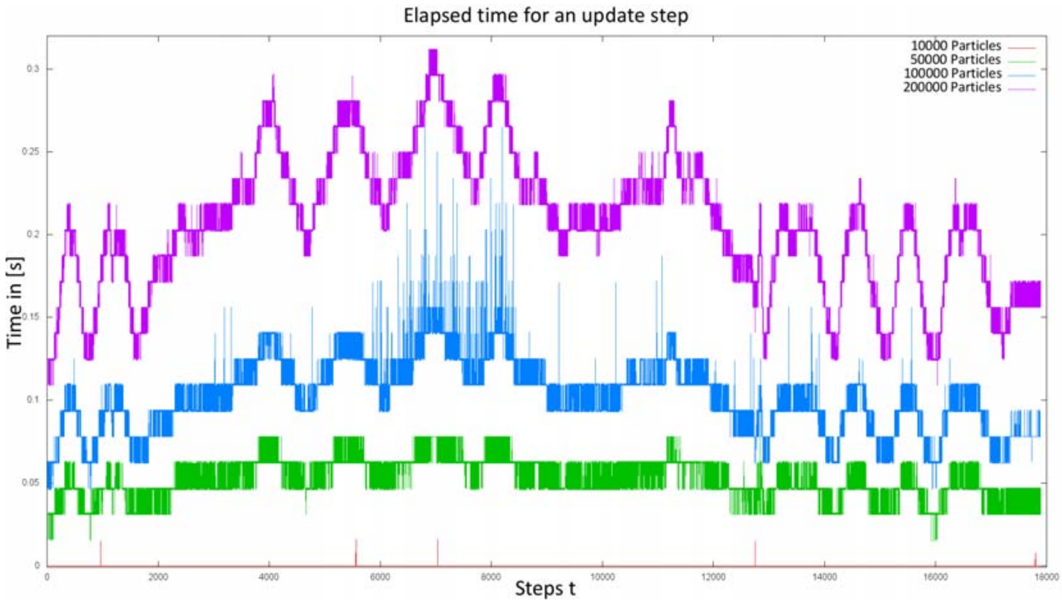

Fig. 3. Time consumption depending on the size of the particle set [own study]

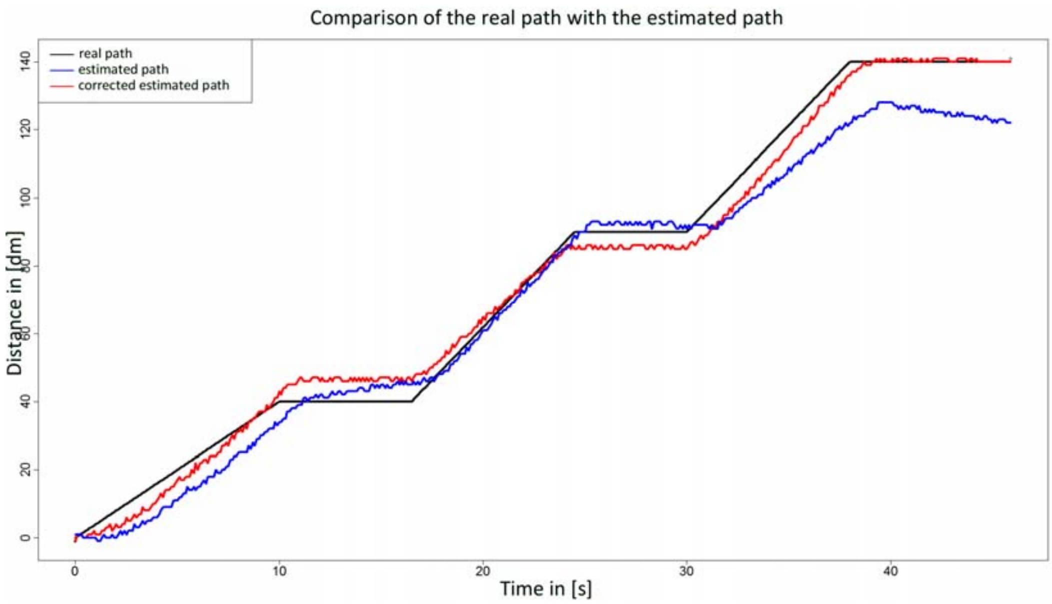

Fig. 4. Linear walk of a total of 14 m with pauses after 4 m and 9 m [own study]

With this result in mind it will be a must to include auxiliary information into the particle filter in the future, which can stabilize the position estimation. Despite the so called 'Curse of dimensionality' the computational performance of our system and the flexible technique of particle filtering leave the door open to this.

CONCLUSION AND FUTURE WORK

In this paper we presented an indoor localization approach using the particle filter technique. The particle filter was tested with data from multiple sensors, namely accelerometer, gyroscope and magnetometer. Our experimental results show that the particle filter returns a positional estimation with high accuracy if the sensor measurement error is not too big. The experiments also show that sensor data alone will not be enough to make an indoor localization possible over a longer period of time.

Instead, additional data like velocity or acceleration have to be integrated into every particle. This will be the focus in our future work. Besides this, we will concentrate our efforts on the use of smartphones and tablets.

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