Real-time 3D Indoor Localization

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Abstract—we present real time indoor localization in the multi-story building using 3D particle filter. Filtration takes place in three dimensional space. Presented method incorporates information from inertial sensors, Wi-Fi signal strength, barometric and building data. We also describe additional methods for determining final locations. Algorithm was tested in multi-story office building and results show that it performs better than particle filters running in two dimensional spaces. Furthermore we propose novel incorporation of floor detection algorithm into particle filter.

Keywords—Wi-Fi; PDR; LBS; 3D Particle Filter; Indoor Localization

I. INTRODUCTION

Indoor Positioning is beginning to play important role in modern world. We spend more and more time indoors. Our buildings grow higher, bigger and their structure is gaining complexity. We observe growing need for location based services targeted both for public and private sectors like personal navigation, tracking people and devices, routing and detection of presence. More researchers bring social aspects of indoor positioning. Koshima et al. [1] discusses the importance of positioning technology to the society. Along with the development of new devices, a great progress in the field of indoor positioning has been observed. Increased capabilities of mobile devices like smart-phones (higher computation power, bigger memory, new cameras), allow the user to use virtual and augmented reality features, which opens up new possibilities for them. It also brings new challenges for researchers.

In this paper we present positioning system that is based on previous work [2]. It is still the solution that relies on existing Wi-Fi infrastructure in the building, requires floor-plans to be available and is targeted for smart-phone devices as it utilizes multiple sensors including accelerometers, gyroscopes and barometers. Methods incorporated include Pedestrian Dead Reckoning (PDR), Wi-Fi based positioning and Particle Filter (PF) which fuses information from previous methods with those obtained from indoor floor-plans. System developed in past years has been improved and extended with new features. The most relevant feature is particle filter working in continuous three dimensional space. System has been tested in multiple locations. Results of our field tests are promising. We observed that accuracy of developed localization methods is stable, hence the results do not vary much when the system is operating in different floors of the same building or different buildings altogether.

Research presented in this paper is aimed to give solutions to three problems:

- Real-time indoor localization in multi-story buildings
- Resampling in 3D Particle Filter (PF) related to transitions between floors.
- Estimating final position from the cloud of particles

Paper is structured as follows: In section II we examine papers that were closely related to our research. Section III presents overview of our solution and highlights new features that differentiate it from other systems. Section IV describes experimental procedure and presents test results. Section V includes discussion of the results, conclusion of work and plans for future research.

II. RELATED WORK

Among wireless technologies in indoor positioning field, bluetooth [3] and Wi-Fi [4][5] are popular subjects of the research. From the range of Wi-Fi features we decided to utilize Received Signal Strength (RSS). Variety of localization methods and techniques has been proposed in this broad scope. Selected method depends on the application and data at hand. For example if locations of Access Points (AP) are unknown, the common technique is to survey the area in off-line phase, record the data and reuse it in the future on-line phase for the purpose of location reckoning.

A. Wi-Fi based positioning

Fingerprinting is the method of gathering and storing Wi-Fi data. In this method, the device performs a Wi-Fi scan and saves the list of AP (or Basic Service Set Identifiers - BSSID's to be precise) along with received signal strength indicator (RSSI) values complemented with precise location of the scanning device. This procedure of scanning can be repeated many times in multiple locations. As the result, one receives set of scan data called radiomap. Radiomap creation and structure itself was the subject of many publications [6][7]. Wi-Fi scanning consumes a large amount of energy which is a big problem as capacity of batteries on mobile devices is...
limited. The problem was addressed in [8]. On-Line (positioning phase) was also addressed in many papers. The most popular method used for the purpose of location estimation seems to be k Nearest Neighbors (kNN) proposed in [9]. On the other hand if location of APs are known, then methods that rely on path loss model described in [10] are commonly used. In path loss formula we can calculate distance from the transmitter (AP) to the receiver (mobile device) assuming measured RSSI level and estimated model parameters. Distances from multiple sources might be then passed to the filter responsible for estimation of receiver location. In current work we utilize path loss model along with trilateration to estimate locations based on Wi-Fi signals.

B. Pedestrian dead reckoning

PDR is the method determining position from the length of the path travelled by the user and the heading changes detected on this path. There are many papers that address correct step detection [11][12][13]. However, not all the authors put proper attention to false-positive steps detection problem, which is called "over-counting" by F. Gu et. al in [14], who proposes analysis of three features of gait: periodicity, similarity and continuity. He proved superiority of his solution over those incorporated in commercial products. Step length estimation for foot mounted devices was covered by Q. Ladetton in [15]. Step length on mobile devices is usually calculated as duration of step time multiplied by constant value. Mentioned constant value can be empirically determined. Heading estimation was covered in [15]. In [16] authors propose solution in which wrong gyroscope information caused by the changes of the smartphone's positions is excluded. For the purpose of step detection and heading estimation in current work we use accelerometer and gyroscope.

C. Floor determination

Method for floor determination in indoor positioning systems can be found in [17]. Incorporation of information from barometric sensor is very popular in algorithms of floor changes detection. Formula for calculation of barometric pressure can be found in [18 Ch. 2.1]. Application of barometer was introduced in [16][19][20][21]. Authors of [19] claim that their fusion algorithm achieved perfect floor detection in three story office building. What is worth mentioning is that building had no Wi-Fi infrastructure installed on the second floor. In our work we use Wi-Fi based ranking list. In addition barometric sensor information is helping in detection of floor changes.

D. Particle filter

PF was widely discussed in [22]. In the literature we can find application of PF to the problem of localization on multiple floors [16][10]. Moreover building information (accessible areas, walls, doors, etc.) find usage in the filter. Nurminen in [10] includes some additional information about floor height and the location of spaces that allow floor change. In this paper we use 3D Particle Filter (particles and obstacles are considered in three dimensional space) and we introduce Vertical Transition Areas (VTA) as the areas on the floor in which floor change of the particles is permitted. Particle Filter fuses in real time smartphone data from Wi-Fi, PDR, barometer and building floor plans and then pass cloud of particles as input to the last filter responsible for determining final locations.

III. PROPOSED ALGORITHM

We propose extended real-time particle filter solution for indoor positioning. It uses Wi-Fi based positioning, pedestrian dead reckoning, atmospheric pressure measurement and floors information to provide user location. System components are presented on Fig.1.

![System components](image)

**Algorithm performs simultaneous positioning in whole venue instead of common multi-level approach in 2.5D particle filters (floor detection → single floor positioning)[20]. It was expected that such solution can improve indoor positioning in multi-story buildings, especially shortly after floor change. Objective of algorithm is estimation of hidden state:**

\[
q_t = (x_t, y_t, z_t, F_t, \alpha_t)^T; x_t, y_t, z_t, \alpha_t \in \mathbb{R}, F_t \in \mathbb{N} \tag{1}
\]

Where \(x, y, z\) represents 3D location on the floor \(z\) is height above the floor, \(F\) is floor number and \(\alpha\) is user heading – all from the same time moment \(t\). All major components of the algorithms are described below:

A. Venue information

Information about indoor environment are widely used in indoor positioning solutions based on particle filter [23][24][19][25]. Knowledge about location of obstacles both improves accuracy and may prevent calculated location from occurring in inaccessible areas. In 3D approach assuming continuous positioning, information about places where floor can be changed (staircases, elevators, escalators) and floor heights are also needed. This additional knowledge enables particles to smoothly transfer between floors. We use dedicated web application that allows upload of floorplans and creation of indoor map on the top of them. As a result we receive 3D venue model used in positioning algorithms. Detailed overview of building model used in our algorithm is described below.

1) Indoor map information

First type of map information used in our algorithm represents all inaccessible areas existing on single floor. As inaccessible areas we define : walls, closed rooms and furniture, all having full floor height. Such floor plan data are often used in particle filters: after each step algorithm
checks whether particle crossed the wall or optionally lies inside obstacle – if it does, its weight is changed to zero. Thanks to this process only particles located in accessible areas "survive" and are used in further computations. It significantly improves accuracy of particle filter algorithms used in indoor positioning, especially in areas with many walls and furniture [10].

2) Vertical transition areas

In 3D approach, information about floor and ceiling are necessary as particles can move vertically along z-axis. On each floor VTA are defined which determines holes in the floor through which particles can transfer to the floor below (Fig 2). Transfer to the floor above is realized by the VTA defined on the floor above.

![Vertical Transition Areas](image)

Obtained above 3D venue model is used in particle filter: after each vertical step, algorithm checks whether newly estimated z-coordinate of the particle is greater than the floor height (lower than zero). If it does and particle is not located in VTA, its weight is set to zero. Otherwise if the particle is located inside VTA it is transferred to another floor.

3) Access Points

For the purpose of Wi-Fi positioning, information about AP are obligatory. Every radio signal transmitter used for positioning needs to have defined location (x, y coordinates and floor number). Transmitted signal strength and path loss exponent are additional AP parameters.

B. Particles distribution between floors

In multi-story building in each Wi-Fi scan there are usually signals from AP located on many different floors. To use PF the following procedure is implemented in many known solutions: first, some floor detection algorithm recognizes current floor [20] and then PF is performed on this single floor [23][24]. We propose different approach where particles in PF are distributed in the whole building. The problem of estimating number of particles on particular floor we solved introducing score formula:

\[
S = \sum_{i=1}^{N} 10^{\frac{p \cdot \text{RSSI}_i}{10 \cdot N}}
\]  

Where S is a score for selected floor, p, N are constant, RSSI, is a signal strength of \(i\)th AP, and summation is after all AP on selected floor. Having received scores for all floors, we normalized them to unity, and then we assume that normalized scores correspond to particles distribution in the venue. We emphasize that probability distribution calculated in this way is used to share particles among floors during initialization and later in global resampling.

C. Wi-Fi filtering

Signal strength based location estimation is very important part, necessary in observation phase of particle filter. In our solution position of device is computed using Multi Algorithm Approach mentioned in [2]. All algorithms use standard path loss model to determine approximate distance between transmitter and receiver. Transformed path model equation which enables conversion of measured signal strength to distance is given by formula (3)

\[
d = 10^{\frac{A - \text{RSSI}}{10 \cdot n}}
\]

Where \(d\) is distance between transmitter and receiver, \(A\) is transmitter signal strength, RSSI is measured received signal strength and \(n\) is path loss exponent. Because of high fluctuations we decided to apply smoothing to RSSI signal. Our smoothing filter is a combination of moving average and median filter. It gives better result than simple averaging because median is strongly resistant to outliers. Wi-Fi locations are calculated for every floor (if possible) and particles weights are updated with formula (4).

\[
w_{t+1} = w_t \cdot P(pos_p, pos_{wifi})
\]

Where \(w_{t-1}\) is new weight, \(w_t\) is previous weight, \(pos_p\) is particle position, \(pos_{wifi}\) – location calculated by Wi-Fi algorithm and P is position probability function based on normal distribution.

D. Pedestrian dead reckoning

Thanks to inertial motion sensors mounted in smartphones it is possible to estimate movement of the device holder. Step detection, step length estimation and heading change detection algorithms are described in our previous article [2]. Horizontal translation and rotation is applied to each particle according to following equation (5):

\[
\begin{bmatrix}
x_{t+1} \\
y_{t+1}
\end{bmatrix} = 
\begin{bmatrix}
x_t \\
y_t
\end{bmatrix} +
\begin{bmatrix}
d \cdot \cos(\Phi) \\
d \cdot \sin(\Phi)
\end{bmatrix}
\]

Where: \(x, y\) are coordinates of particle in time, \(d\) is calculated step length and \(\Phi\) is heading angle. Both \(d\) and \(\Phi\) are distorted with normal distribution. Afterwards, weights of particles are updated using floorplan data.

E. Altitude change filter

Recently more and more modern smartphones are equipped with a barometer sensor. It has been proven that the
accuracy of this sensor is good enough to detect significant and rapid vertical movement of mobile device [26]. Using barometric formula we can calculate relative altitude change on the basis of measured pressure change (6):

$$\Delta h = -\frac{R \cdot T}{M \cdot g} \cdot \ln \left( \frac{p}{p_0} \right)$$  \hspace{1cm} (6)

where $R$ is universal gas constant, $T$ is standard room temperature (20°C), $g$ is gravitational acceleration, $M$ is molar mass of Earth's air, $p$ – current pressure value, $p_0$ – baseline pressure. Every sensor reading fluctuates and atmospheric pressure changes over time, thus we applied moving average on pressure readings. We also introduced a threshold for height difference and exceeding this value is considered as a vertical step. Detection of vertical step entails assigning a new baseline pressure. Finally barometer data effects on 3D PF in the following way: value of vertical step (distorted with normal distribution) is added to each particle vertical location then using venue information (especially VTA) we can calculate new particles distribution in the venue.

F. Global resampling

As mentioned before, after every Wi-Fi scan probability for each floor (scores distribution) is calculated. If this distribution differs significantly from current particles distribution, particles are taken from floors for which probability decreases and are moved to more probable floors. Difference between distributions is computed using Euclidean distance. Location in XY and heading of each particle doesn't change so this information is not lost after floor change.

G. Local resampling

Whereas particles become negligible during PDR and vertical movement updates, resample phase is necessary to avoid sample depletion. When effective number of particles (defined in [25]) on the floor decreases below defined threshold, resampling algorithm is applied: some particles are recreated in neighborhood of last location computed with Wi-Fi algorithm. It is allowed for the particles to be resampled on different floors.

H. Final location estimation

Result of PF is no single location, but cloud of particles. Therefore, last step of our indoor positioning solution has to be estimation of single, most relevant position. As PF is running on many floors, first stage must be the selection of current floor. It's done simply by choosing floor with the highest effective number of particles. As number of particles on each floor does not depend directly on current location of Wi-Fi scan, floor detection works stable even in open environment with APs from different floors visible. Having set of particles on chosen floor final filter is applied. Different estimators were implemented and tested:

1) Mean position estimator

Final location is calculated as weighted average of positions of all particles located on considered floor. This method, despite its simplicity, gives very good accuracy. However it has one disadvantage in terms of user experience: position very often appears in inaccessible areas.

2) Ant colony position estimator

Each particle spreads “pheromone” (equal to the value calculated on the basis of particle weight and Gaussian kernel) in its surrounding and the highest sum of “pheromone” is considered as final location. Full description is presented in [2].

3) Clustering Position Estimator

Instead of calculating position from all particles this method searches for clusters of particles that are close to each other. In order to determine particle neighbors we are using grid and check neighborhood of cell edges. Next we select the cluster with the highest sum of particles weights. The final position is estimated as weighted mean position from all particles in the final cluster (Fig. 3).

![Cluster of particles](image)

4) Clustering position estimator with heading filtering

Compared to 3) this version additionally takes particles heading into account. We create heading distribution based on particles weights. When the heading is considered stable, we keep only particles which heading is consistent with the dominant heading. In the next steps we calculate position as defined in clustering position estimator.

Results of positioning accuracy for all final location estimators mentioned above are compared in Tables II and III.

IV. FIELD TESTS AND RESULTS

A. Tests description and methodology

Tests were performed in the Warsaw Spire Office Building, Warsaw, Poland. The test contains 17 tracks that were completed on three floors by 3 different users (3 tracks on a single floor, 13 tracks between two floors, and one track between three floors). The devices used to record those tracks are: Samsung Galaxy S6, Samsung Galaxy Note 3 and Samsung Galaxy Note 5.
Each floor contains different number of access points used for positioning. Detailed list of access point number is described in Table I.

<table>
<thead>
<tr>
<th>Floor</th>
<th>AP number</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>24</td>
</tr>
<tr>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>21</td>
<td>19</td>
</tr>
</tbody>
</table>

During the test the following data were recorded with corresponding timestamp:
- Accelerometer sensor values
- Gyroscope sensor values
- Pressure sensor values
- Wi-Fi scans
- Ground truth location – control points set manually by the tester

The same recorded data were used for calculating positions for different versions of algorithms. It gives exactly the same conditions for all versions, what makes comparison of algorithms objective.

In order to determine the algorithms efficiency we are calculating Euclidean distance in two dimensional space between calculated point and predicted ground true location at a certain timestamp see Fig. 4.

![Fig. 4. Errors calculation](image)

The ground truth locations indicates tester path. Some of the paths were created between floors. Path segments that connect two floors were ignored in error calculation.

### B. 3D and 2D Particle Filters comparision

Tables II and III presents test result comparison between 2D and 3D particle filter with different methods of calculating final position from particles clouds.

<table>
<thead>
<tr>
<th>Final location estimator</th>
<th>Mean</th>
<th>CEP 50</th>
<th>CEP 68.27</th>
<th>CEP 95.45</th>
<th>CEP 99.73</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.684</td>
<td>1.362</td>
<td>1.925</td>
<td>3.919</td>
<td>11.628</td>
</tr>
<tr>
<td>Ant colony</td>
<td>1.808</td>
<td>1.347</td>
<td>2.044</td>
<td>4.669</td>
<td>12.066</td>
</tr>
<tr>
<td>Clustering</td>
<td>1.746</td>
<td>1.311</td>
<td>1.915</td>
<td>4.498</td>
<td>11.977</td>
</tr>
<tr>
<td>Clustering with heading</td>
<td>1.746</td>
<td>1.319</td>
<td>1.949</td>
<td>4.477</td>
<td>11.857</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Final location estimator</th>
<th>Mean</th>
<th>CEP 50</th>
<th>CEP 68.27</th>
<th>CEP 95.45</th>
<th>CEP 99.73</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.383</td>
<td>1.122</td>
<td>1.592</td>
<td>3.571</td>
<td>6.489</td>
</tr>
<tr>
<td>Ant colony</td>
<td>1.431</td>
<td>1.013</td>
<td>1.564</td>
<td>4.059</td>
<td>7.29</td>
</tr>
<tr>
<td>Clustering</td>
<td>1.356</td>
<td>1.031</td>
<td>1.511</td>
<td>3.729</td>
<td>7.48</td>
</tr>
<tr>
<td>Clustering with heading</td>
<td>1.357</td>
<td>1.004</td>
<td>1.479</td>
<td>3.795</td>
<td>7.629</td>
</tr>
</tbody>
</table>

From Tables II and III we can conduct that accuracy is better in 3D algorithm for all final location estimators. The biggest advantage of 3D particle filter is that the particles keep XY-locations and headings when they are moving between floors. In 2D version of algorithm the particles were generated afresh after floor change. In this situation the global heading needs to stabilize once again, even though on the previous floor majority of the particles had steady heading. To sum up, in 2D approach position is inaccurate every time the floor changes and in 3D PF it has to stabilize only once when positioning service starts. It can be observed in Fig 5. and is also confirmed in significant decrease of CEP99 value. Another problem that might occur is significant displacement between VTA and calculated position which mostly depends on the Wi-Fi positioning accuracy (Fig. 5). In our testing environment the pressure shows little impact on positioning accuracy. However altitude change filtering presented in this paper might be useful when there are many strong AP’s signals visible from different floors or in places where access points are not visible at all.

![Fig. 5. State of 2D PF(left) and 3D PF (right) after floor change](image)
C. Final location estimators

In open-space offices we can find many corridors between desks. In such places the particles might split into groups and each group relocates to different corridor (Fig. 6).

![Particles split between desks](image)

The Fig. 7 presents how different position estimators handle situation from Fig. 6. The mean position estimator has the tendency of estimating positions inside desks. The other estimators can cause visible jumps between corridors.

![Final location estimators-1. Mean (top left), Ant (top right), cluster (bottom left), cluster with angle (bottom right)](image)

The Fig. 8 depicts how particles behave at the beginning phase of the positioning. Due to the fact that heading is not stabilized yet the particles divide into groups. The particles in each of the groups tend to keep similar heading.

![Particles (left) and particles headings (right)](image)

Fig. 8. Particles (left) and particles headings (right)

![Particles angle (heading) density](image)

Fig. 9. Particles angle (heading) density

Fig. 9 presents particles heading distribution. We can see two peaks in around 40 and 310 angle values. One of them represents most probable global heading. Over the time the number of particles with correct heading should increase. Instead of using only quantity and weights of particles in estimating final location, the heading information is valuable, especially in situations when there is disproportion between the number of the particles and their headings (Fig.8). Fig. 10 demonstrates how different estimators handle the situation. There is noticeable jump to incorrect corridor in ant colony and cluster position estimators. Those estimators take into account concentration of particles but avoid angle information in calculating final position. Using angle filtering allows increasing the chance of selecting correct cluster of particles.
D. Wifi smoothing

In order to increase the Wi-Fi positioning accuracy Wi-Fi signal are filtered. Fig. 11 presents Wi-Fi positions calculated with Wi-Fi smoothing filter disabled and enabled. Positions calculated from filtered signal scans looks more continuous. Filtering also significantly reduced positioning errors (see Table IV). Table IV present the results of Wi-Fi positioning algorithm alone.

![Fig. 10. Final location estimators - from the start. Mean (top left), Ant (top right), cluster (bottom left), cluster with angle (bottom right)](image)

![Fig. 11. Wi-Fi smoothing disabled (left) and enabled (right)](image)

TABLE IV. RESULTS OF WI-FI SMOOTHING

<table>
<thead>
<tr>
<th>Test</th>
<th>Mean</th>
<th>CEP 50</th>
<th>CEP 68.27</th>
<th>CEP 95.45</th>
<th>CEP 99.73</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoothing off</td>
<td>3,029</td>
<td>2,674</td>
<td>3,608</td>
<td>6,84</td>
<td>11,039</td>
</tr>
<tr>
<td>Smoothing on</td>
<td>2,315</td>
<td>1,974</td>
<td>2,663</td>
<td>5,396</td>
<td>9,164</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS AND FUTURE WORK

We described a real time indoor localization in the multi-story building using 3D particle filter. We have shown that our new solution provides better positioning accuracy in multi-story environment with comparison to previous solution [2]. We have also described improvements that can be used in both 2D and 3D particle filter. One of the approaches that can be done in future work is activity recognition. Depending on the type of VTA the user behaves differently and such information can be used to improve floor change detection or to add new conditionals to particle filter. Another approach is not to use only one but multiple location estimators to calculate final position from particles.

References

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