A New Method for Indoor Positioning Based on Integrating Wireless Local Area Network, Bluetooth Low Energy, and Inertial Sensors

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Increasing the accuracy of indoor positioning is still a challenging issue. In this paper, we propose a novel integration structure for indoor positioning using a wireless local area network, Bluetooth low energy beacons, and inertial sensors to increase the positioning accuracy. The main steps of this method are initial and relative positioning. Wireless local area network fingerprinting and database filtering using Bluetooth low energy are applied to calculate the initial location. Relative location is computed using inertial sensors data and the pedestrian dead reckoning method. In order to increase the accuracy of pedestrian dead reckoning, two sources of information, wireless local area network, and Bluetooth low energy are used. This new correction method is performed using a double Kalman filter. Extensive experiments were conducted in a smartphone and under two indoor environments. Our correction structure using a double Kalman filter outperforms previous pedestrian dead reckoning structures in terms of accuracy. Moreover, experimental results show our correction structure achieves an average accuracy of 1.7 meters.

Keywords. Indoor positioning, Wireless Local Area Network (WLAN), Bluetooth low energy BLE), Pedestrian Dead Reckoning (PDR), Kalman filter, Data Fusion.

1. Introduction

Most people spend more than 70% of their time in indoor areas (Y. Li et al. 2017). Thus, location-based services are highly demanding in indoor areas,

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especially in hospitals, airports, train stations, and shopping malls (Evennou and Marx 2006). These location-based services require indoor positioning and tracking systems (Mohammad R. Malek and Frank 2006; Carrera V. et al. 2018). Various indoor positioning methods using Wireless local area network (WLAN) (Vahidnia et al. 2013; Ma et al. 2015; Khalajmehrabadi, Gatsis, and Akopian 2017), Ultra-wideband (UWB) (Garcia et al. 2015), ZigBee (Niu et al. 2015), Bluetooth low energy beacons (BLE) (Röbesaat et al. 2017), Radio frequency identification (RFID) (H. Xu et al. 2017), and inertial sensors (Orujov et al. 2018; L. Xu et al. 2019), have been developed.

Any of these methods have limitations and disadvantages such as low accuracy, high cost to provide the required hardware or computational complexity. Moreover, there exists no technology that works perfectly in different buildings. Therefore, recent investigations have been conducted on improving indoor positioning (Röbesaat et al. 2017). Among all solutions, integrating different indoor positioning techniques is an optimal solution for increasing accuracy and reducing the limitations of every single method (Y. Li et al. 2017; Poulose, Kim, and Han 2019). In this paper, we propose a novel integration structure for indoor positioning using wireless local area network, Bluetooth low energy beacons, and inertial sensors to increase the positioning accuracy.

2. Related work

Several hybrid indoor positioning research using WLAN, BLE, and inertial sensors are discussed in this section. These researches combine information from two or all of these sources. Li et al. (2015) proposed two fusion structures using BLE data and PDR method. The first structure is determining location, using PDR and map matching, then correct it using the BLE data. The second structure is combining PDR and BLE using adapted noise extended Kalman filter. The results showed that both fusion structures have higher accuracy than single positioning algorithms. Li et al. (2017), proposed a hybrid indoor positioning algorithm using WLAN, PDR, and Magnetic matching.

Some researchers have focused on combining an absolute indoor positioning, such as WLAN or BLE, with a relative indoor positioning such as PDR (Orujov et al. 2018). Chen et al. (2015) proposed a hybrid indoor positioning method using the WLAN fingerprinting and PDR method.

A few number of research studied the hybrid indoor positioning structures using BLE, WLAN, and PDR. Zou et al. (2017) introduced a fusion structure using WLAN and BLE observations and inertial sensors data using a particle filter. They fused WLAN and inertial sensors data to reduce the drift of indoor positioning and in poor coverage of WLAN signals; they utilized BLE RSS to correct PDR. Chen et al. (2016) proposed a smartphone based indoor positioning method with BLE corrections using an extended Kalman filter. This article studied step detection, step length estimation, and walking direction estimation.

In our study, we used two different RF-based observations to reduce the PDR drift. Some of the presented research, such as Frank et al. (2009) and Zou et al. (2017), require processing on a server or special equipment. However, we introduced a method that can be run on smartphones without additional hardware. Some articles like Kanaris et al. (2017) only calculate the absolute location and do not consider real-time positioning. The purpose of this study is to solve the mentioned problems and limitations by combining WLAN and BLE RSS measurements and PDR method.

3. Preliminaries

The fingerprinting method is a positioning method, which uses the RSS measurements of RF signals. In the first phase, RSS measurements are collected, for example, from WLAN APs, and stored in a database called radio map. Then in the second phase, real-time collected RSS matches with radio map to estimate the location using definite or probabilistic methods (Vahidnia et al. 2013; Deng et al. 2015)

Vector of N measured RSS measurements at the unknown point from defined APs and vector of collected RSS measurements at the j-th RP from defined APs, respectively are $\boldsymbol{s}$ and $\boldsymbol{r}_i$. Equation 1 shows the Euclidean distance between the i-th reference point and the unknown point.

$$d_j = \sqrt{\sum_{i=1}^{n}(\boldsymbol{r}_{ij} - \boldsymbol{s}_i)^2} \qquad (1)$$

$\boldsymbol{s}_i$ and $\boldsymbol{r}_{ii}$ are the i-th element in $\boldsymbol{s}$ and $\boldsymbol{r}_i$, respectively. K nearest RPs are selected for positioning using Weighted K-Nearest Neighbour (WKNN). Then the weighted average of k nearest neighbours' positions estimates the unknown location.

PDR is a relative positioning method that uses previous position, step length, and direction to calculate the current position. Equation 2 shows the

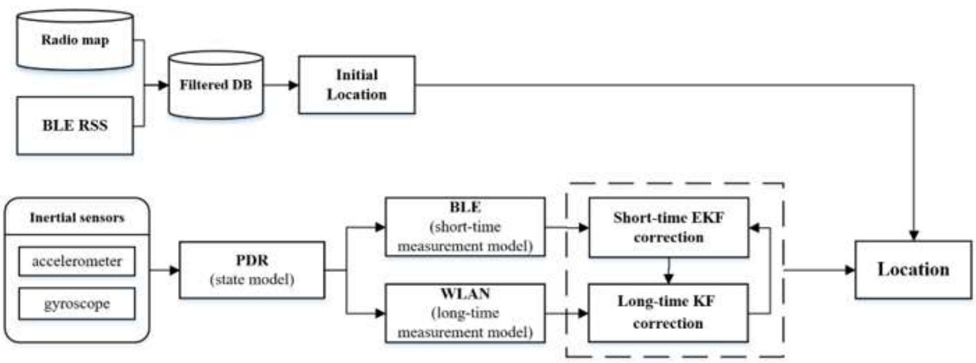
PDR formula. In this equation, $\boldsymbol{x}_k$ is a two-dimensional coordinate vector of the previous position, l_K is step length, θ_k is step heading, and $\boldsymbol{x}_{k+1}$ is estimated coordinate vector (Malek 2020).

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + l_K \begin{bmatrix} \sin\theta_k \\ \cos\theta_k \end{bmatrix} \quad (2)$$

Where, $\boldsymbol{x}_i$ is the position vector of j-th RP, $\hat{\boldsymbol{x}}$ is the estimated position vector, and d_i is calculated using equation 2.

4. Proposed method

Our proposed method is shown in **Error! Reference source not found.** which mainly consists of initial positioning, PDR, and PDR correction. Initial location is calculated using WLAN fingerprinting and BLE measurements. Radio map is filtered using the nearest BLE beacons RSS measurements. Finally, the initial location is estimated using the WKNN algorithm. PDR calculates Relative displacements of the user using gyroscope and accelerometer data. A Kalman filter with two measurement equations corrects PDR using WLAN and BLE observations. PDR, BLE observations, and WLAN measurements estimate the state equation of the Kalman filter, short-time measurement observation, and long-time measurement obser-



vation, respectively.

Figure 1. Overview of the proposed indoor localization approach.

4.1. Initial positioning

The Fingerprinting method is used to calculate the initial location of the user. To reduce blunders and decrease the search time in the database, BLE RSS measurements filter the WLAN fingerprinting database.

We used a one-dimensional Kalman filter for BLE RSS filtering and increasing positioning accuracy. Then a second order polynomial equation is used to model the distance between nearest beacon and user based on BLE RSS measurements. This polynomial equation is built after collecting data at different distances from each beacon and using least square estimation. Equation 3 shows a function for estimating the distance from a beacon.

$$r_i = 0.0073{rss_i}^2 + 1.012rss_i + 10.4 \qquad (3)$$

In equation 3, rss_i is the RSS from i-th beacon at an unknown location, and r_i is the estimated distance from i-th beacon. After comparing estimated distances from each beacon, the nearest beacon is detected, and based on the estimated distance to the nearest beacon, WLAN fingerprinting database is filtered. Thus, instead of searching in a large database, a smaller set of RPs is selected as the search area in the WKNN algorithm. The final initial location is calculated using the WKNN method.

4.2. PDR correction

PDR method is simple and common but suffers from drifting problems (Poulose et al. 2019). It has a cumulative error which increases over time. In order to reduce the cumulative error of PDR, we used a double correction method. WLAN and BLE measurements are used to correct PDR, and Kalman filter is used to fuse information. To use both observations, two different time intervals for using each measurement are defined. Because of the higher sampling rate of BLE measurements, we used them for short-time correction. WLAN measurements are used for long-time correction and when BLE RSS measurements are weak. We define each step as a short-time interval and every 12 steps as a long-term interval. Figure 2 shows the correcting process.

In our algorithm, after detecting a step, step length and heading are estimated using real-time accelerometer and gyroscope data. If the number of steps is not a multiple of 12, measurement mode is set to BLE. Then BLE RSS measurements are collected and distance to each beacon is estimated. If the RSS of the nearest beacon is more than -95 dBm, the measurement equation of the Kalman filter is defined using the estimated distance to it.

The state equation of Kalman filter is defined using the PDR method and Kalman filter is implemented.

```
PDR correction
Given: accelerometer and gyroscope real-time data, S←number of steps, measurement_mode
if a step is detected:
S++
calculate step length and heading
  if S is not a factor of 12:
      switch measurement_mode to BLE
      collect RSS measurements of beacons
        calculate distance from beacons
       find the nearest_beacon
          if RSS of nearest_beacon <= -95 dBm
             break
          end if
  end if
     if S is a factor of 12:
   collect WLAN RSS measurements of Defined APs
   switch measurement_mode to WLAN
   calculate the estimated_position using WKNN
     end if
 calculate Kalman state equation using PDR
     if (measurement_mode is BLE)
           calculate measurement Eq from BLE
           run Kalman filter
     end if
     else if (measurement_mode is WLAN)
           calculate measurement Eq from WLAN
           run Kalman filter
      end if
end if
go to 1
```

Figure 2. PDR correction algorithm.

If the number of steps is a multiple of 12, measurement mode is switched to WLAN. Then WLAN RSS measurements from APs are collected and the user's location is estimated using fingerprinting and WKNN. Measurement equation of the Kalman filter is defined using the estimated location. Then, the Kalman filter with the PDR state model and WLAN measurement model is executed.

If the RSS of the nearest beacon is more than -95 dBm, the measurement equation of the Kalman filter is defined using the estimated distance to it. If the number of steps is a multiple of 12, measurement mode is switched to WLAN. Then WLAN RSS measurements from APs are collected and the user's location is estimated using fingerprinting and WKNN. Measurement equation of the Kalman filter is defined using the estimated location. Then, the Kalman filter with the PDR state model and WLAN measurement model is executed.

We developed short-time and long-time corrections. A Kalman filter is utilized to correct PDR cumulative error in each step using Bluetooth RSS measurements. In long time correction, WLAN measurements are used to build the Kalman observation model. A long-term correction interval was chosen every 12 steps.

5. Implementation and evaluation

We have developed an android app for real-time positioning and evaluation. The app can be run on any mobile device with a gyroscope, accelerometer, Wi-Fi, and Bluetooth receiver. All steps related to data collection and positioning were performed using the app. In this study, six beacons were used. All beacons were installed at the height of 1.5 meters above the grounds and on the walls. The transmission power for BLE beacons was set to 0 dBm.

The experiments have been carried out at the K.N. Toosi University of Technology. The third floor of the faculty of Geodesy and Geomatics that is in 70×14 m^2 was selected. The environment is a corridor along which there are stairways to the mezzanines, floors, and roof. The corridor is mainly used for walking in a linear path.

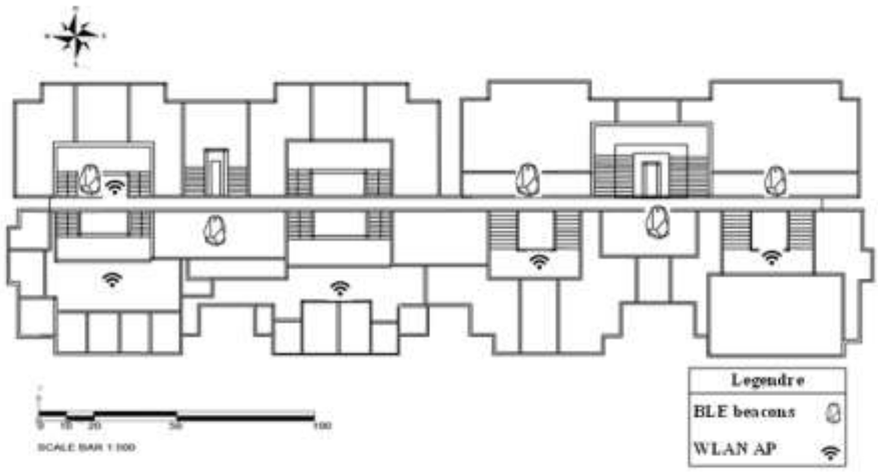


Figure 3. The plan of our case study

Figure 3 shows the experimental environment, location of beacons, and WLAN APs. RPs were selected in in 2×2 m^2 grids. RSS measurements were collected at four directions and 20 times in each direction. Then, the average of RSS readings was stored in the database. The RSS of an unavailable AP is set to -100 dBm. In the environment, 74 RPs using 5 APs were collected.

Initial positioning method using WLAN and BLE observations, PDR using inertial sensors, and PDR corrections using WLAN and BLE observations were performed to evaluate the proposed hybrid method. In this experiment, the user walked along the defined path and estimated locations was compared to the ground truth.

In order to evaluate the initial positioning method, 20 checkpoints were selected. Then, each checkpoints' locations were estimated using the defined method and was compared to the real locations. In Figure 4 real locations of checkpoints, estimated locations of checkpoints, and positioning error for each point are shown using circles, squares, and triangles, respectively. The average initial positioning error was estimated at 2.2 meters. The computational speed of searching in the filtered database increased by an average of 54% Compared to computational speed in the main database.

In Figure 4, the estimated locations using PDR, estimated locations using corrected PDR with BLE and estimated locations using corrected PDR with BLE and WLAN are shown by circles, squares, and triangles in the first environment, respectively. A straight line in Figure 5 shows the true path of walking. PDR cumulative error is corrected twice, and the final positioning error after the two-step correction is less than PDR and short-time correction using BLE.

Figure 6 and Figure 7 illustrate the error of positioning methods at each step and cumulative distribution function (CDF) curves of position errors, respectively. The average PDR positioning error was estimated 4.03 m. After PDR correction using BLE through the Kalman filter, the average positioning error was decreased to 2.3 m. The average positioning error after the proposed two-step correction was reduced to 1.8 m, and the accuracy of positioning was increased compared to the other two methods.

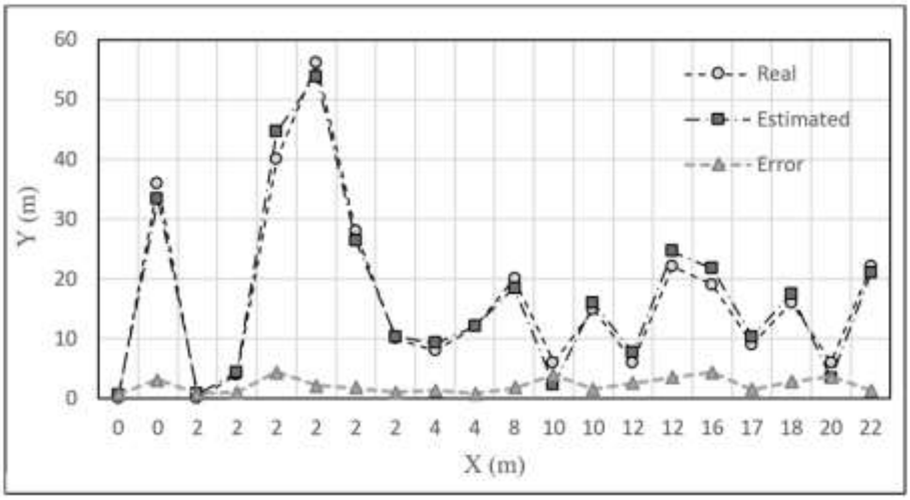


Figure 4. Initial positioning method evaluation (circles: true locations of checkpoints, squares: estimated locations, triangles: positioning error).

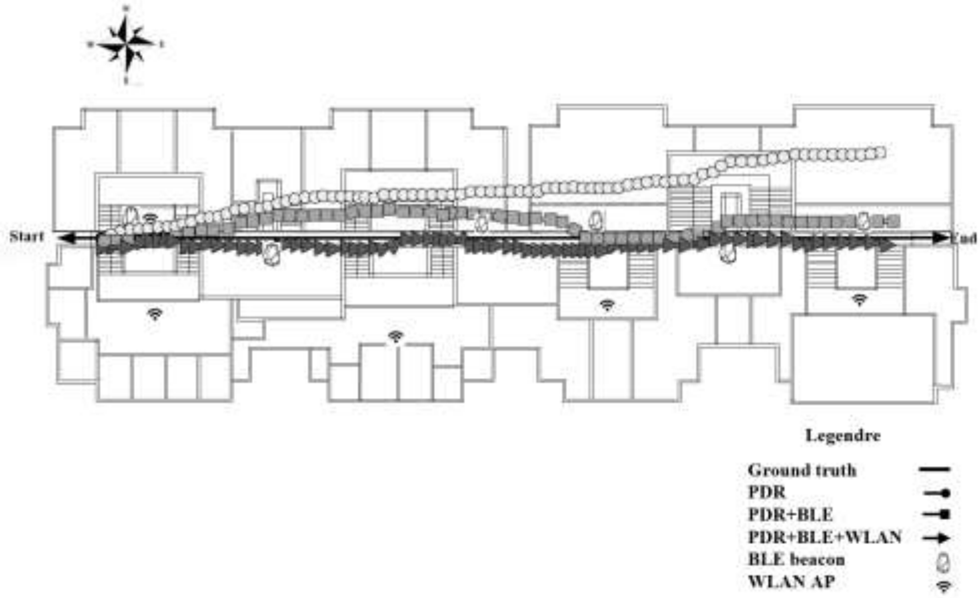


Figure 5. Ground truth and estimated locations using PDR, corrected PDR using BLE, corrected PDR using BLE and WLAN in the first environment.

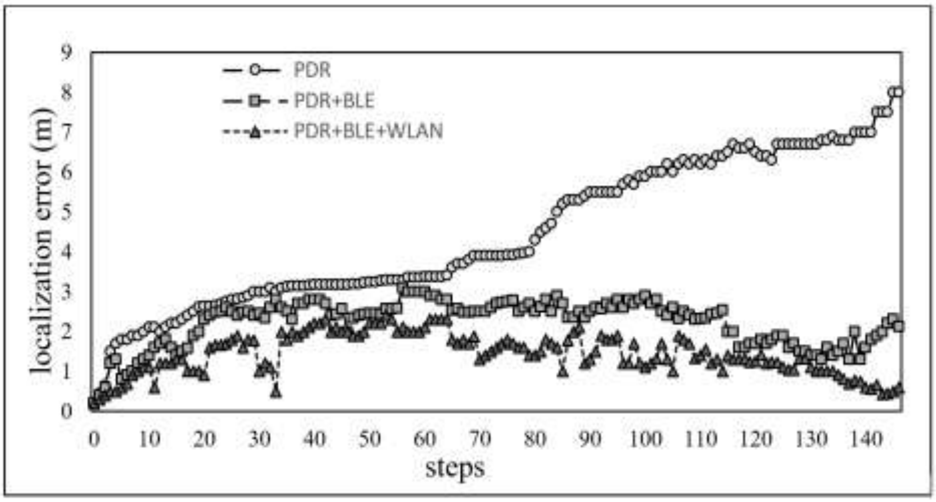


Figure 6. Positioning error of different methods per step.

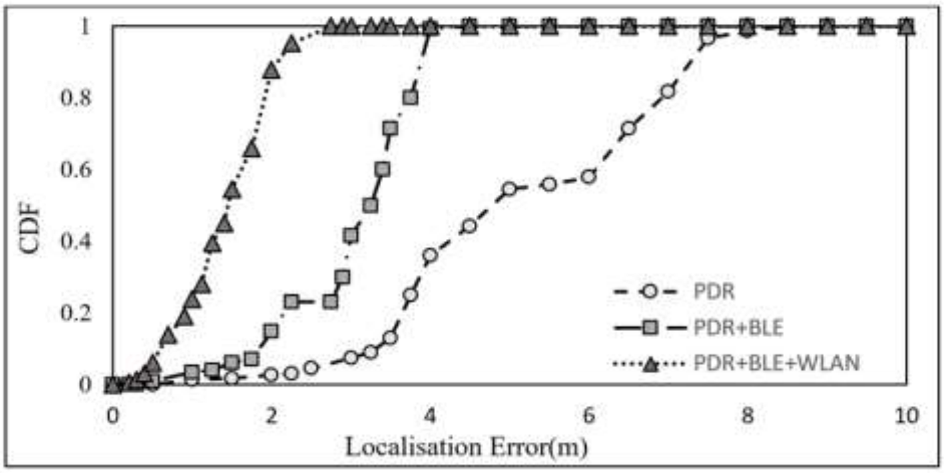


Figure 7. CDF of positioning errors for different methods.

6. Conclusion

In this paper, we proposed an integrated indoor positioning method with inertial sensors, WLAN, and BLE observations. To improve the PDR accuracy and reduce the cumulative error of PDR, we used a novel correction method using WLAN and BLE observations. Because of the high sampling rate of BLE RSS measurements, we used BLE observations for short-time correction, and WLAN observations with a lower sampling rate, for long-time correction. To reduce blunders, BLE RSS measurements were filtered and weak RSS measurements (lower than -95 dBm) were not sent to the correction phase. Moreover, initial positioning was achieved using a filtered fingerprinting database.

The final results of our experiment shows that the average positioning error of PDR correction using BLE and WLAN was lower than PDR and corrected PDR using BLE. The average positioning of the proposed correction method was estimated at 1.7 m, and the highest and lowest errors were about 0.6, and 2.7 respectively. Furthermore, our method could be used for real-time applications.

Future research will focus on improving the proposed method by using other methods like map matching, and we will also examine floor detection.

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