Wi-Fi Node Location Estimation Based on GNSS and Motion Sensor Data

Pavel Ivanov[1], Henri Nurminen[1], Simo Ali-Löytty[2] and Pasi Raumonen[2]

[1]HERE Technologies, Kalevantie 2, Tampere, 33200, Finland
[2]Tampere University, Korkeakoulunkatu 7, 33720, Tampere, Finland

Abstract

Indoor localization is a well researched scientific topic and demanded commercial and technological area. However, the problem of scalability remains for indoor localization systems. Though there is a plenty of radio-based approaches for indoor localization that achieve high level of accuracy, many of those rely on manual data collection which is laborious and not globally scalable. In this paper we approach the problem of scalable radio-mapping by improving estimation of horizontal locations of Wi-Fi radio nodes using GNSS and motion sensor data collected in crowd-sourcing manner, i.e. without manual human intervention. We use simple and yet robust sensor fusion algorithms based on Kalman Filter to estimate pedestrian tracks in indoor and outdoor environments, and then use resulting location estimates as a reference for radio measurements, which are further used to estimate horizontal locations of Wi-Fi radio nodes indoors. We then analyze different radio measurement selection criteria for Wi-Fi node location estimation methods. The experiments based on real data indicate that sensor fusion considerably improves localization of Wi-Fi radio nodes when compared to approaches relying on GNSS data only. Our study also shows that using only radio measurements with strong signal and accurate location reference results in more accurate localization of Wi-Fi radio nodes. The results also indicate that estimation of Wi-Fi radio node locations with accuracy below 15-20 meters on average is achievable without manual data collection, and hence in a globally scalable way. Proposed approaches may be further extended with sensor fusion methods utilizing, for example, misalignment estimation and magnetometer measurements, as well as applied to radio technologies other than Wi-Fi, such as 5G radio technologies.

Keywords

Wi-Fi positioning, Wi-Fi crowd-sourcing, indoor positioning, sensor fusion,

1. Introduction

In this paper, scalable methods for Urban and Indoor localization, and localization of Wi-Fi radio nodes indoors in particular are discussed. Wi-Fi based indoor localization systems use radio maps for location estimation. Experimental results for Wi-Fi indoor positioning systems based on fingerprinting, path loss and coverage area modeling, and manually collected radio data, with accuracy below 10 meters, are presented in [1],[2],[3]. In [4] authors generate indoor radio map by estimating locations of the indoor Wi-Fi measurements based on the outdoor measurements geo-referenced with GNSS and achieve accuracy of around 30 meters. In [5]

ICL-GNSS 2022 WiP Proceedings, June 07–09, 2022, Tampere, Finland
pavel.ivanov@here.com (P. Ivanov); henri.nurminen@here.com (H. Nurminen); simo.ali-loytty@tuni.fi (S. Ali-Löytty); pasi.raumonen@tuni.fi (P. Raumonen)
0000-0002-1859-6805 (P. Ivanov); 0000-0003-0949-8848 (H. Nurminen); 0000-0002-6720-7722 (S. Ali-Löytty); 0000-0001-5471-0970 (P. Raumonen)

authors estimate Wi-Fi signal strength maps based on radio data from partial radio coverage indoors. There are major challenges in indoor radio mapping. First, manual data collection for radio map creation is laborious and not scalable. Second, estimation of radio measurements' or radio nodes' locations indoors based on the outdoor radio data as well as extrapolating radio environments from outdoors to indoors may be challenging because of non-line-of-sight radio propagation modelling.

In this study we make an effort to estimate locations of the radio measurements indoors using GNSS and inertial sensor data. This approach is scalable, but provides noisy location data. We further use geo-referenced radio measurements to estimate locations of Wi-Fi radio nodes, considering this as the first and yet fundamental step towards complete 3D Wi-Fi radio mapping indoors. Typically, wi-Fi access point location can be estimated based on the GNSS-referenced radio measurements with the accuracy of tens of meters, depending on how far the access point is from the area where GNSS signals are observable and where those areas are with respect to the location of the access point. Combining GNSS with inertial sensor data enables us to estimate location references for radio measurements not only in outdoor areas, but also indoors, however, accuracy of such references decreases rapidly after GNSS signals are lost. We further discuss the method for estimating radio nodes' horizontal locations based on radio measurements referenced based on GNSS and inertial sensor data integration.

The paper is organized as follows. In Section 2 method for GNSS and inertial sensor data fusion is outlined. In Section 3 method for measurement aggregation and radio node location estimation is described. Section 4 provides details about experimental setup and results. Section 5 summarizes the study.

2. GNSS and inertial sensors for radio measurements localization

For this study we used pedestrian dead reckoning method based on Kalman Filter presented in [6]. Pedestrian dead reckoning uses accelerometer-based step counting, and gyroscope-based pedestrian heading tracking, where heading is initialized based on GNSS fixes, and then tracked with gyroscope and estimated gravity vector. We define system state at time k as a four-component vector

$$\bar{x}_k = \begin{bmatrix} x_1^k \\ x_2^k \\ x_3^k \\ x_4^k \end{bmatrix}, \tag{1}$$

where x_1^k, x_2^k represent horizontal location at time k, and x_3^k, x_4^k represent so-called step vector, whose direction and norm represent pedestrian heading and step length at time k. Hence, Kalman Filter uses linear state transition model defined as

$$\bar{x}_k = F \cdot \bar{x}_{k-1}, \tag{2}$$

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & \cos(\theta) & -\sin(\theta) \\ 0 & 0 & \sin(\theta) & \cos(\theta) \end{bmatrix}, \tag{3}$$

where θ is the angle by which heading of the pedestrian has changed during the update step. We use GNSS fixes to measure the position components of the state, and measurement model for the Kalman Filter is defined as

$$\bar{z}_k = H \cdot \bar{x}_k, \tag{4}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{5}$$

, where $\bar{z}_k = [z_1^k, z_2^k]^T$ represent horizontal GNSS position.

In addition to standard prediction and update phases of the Kalman Filter, step vector norm is adjusted whenever it gets larger or smaller than predefined limits corresponding to a typical step length. Step length correction is done as follows:

$$\begin{bmatrix} x_3^k \\ x_4^k \end{bmatrix} = l \cdot \frac{\begin{bmatrix} x_3^{k-1} \\ x_4^{k-1} \end{bmatrix}}{\left|\left|\begin{bmatrix} x_3^{k-1} \\ x_4^{k-1} \end{bmatrix}\right|\right|}, \tag{6}$$

where x_3^k, x_4^k are the step components of the state at time k, l is the lower or upper step length limit, depending on whether step length is short of or exceeds the lower or upper limit respectively.

With this method we do not estimate so-called misalignment, which is the orientation of the device with respect to the user. Instead, heading change θ in state transition model (3) is set to zero when misalignment change is detected, and filter process noise, namely for the step components, is increased. As a result, position estimation may deviate from the true user track in cases when pedestrian makes a turn concurrently with changing device misalignment, but location estimate co-variance will be increased and remain consistent with the possible location error of the data sample[[6]]. As a result, such uninformative data samples will have low weight in further estimation process, or can be discarded completely. In general, we make an assumption that given large number of user tracks, at least some of those will contain parts where device misalignment remains constant, at least for several (1-5) minutes when going from outdoors to indoors, which is sufficient to cover an indoor area from entrance to the final destination within the building:office/shop/apartment.

3. Radio data aggregation and Wi-Fi radio node location estimation

We estimate Wi-Fi radio nodes' locations based on large amount of radio measurements, from tens of user tracks, primarily because of the low localization accuracy for an individual tracks. Potentially large error in the location reference of an individual measurement is compensated by aggregating large number of measurements with presumably evenly distributed error, whose mean eventually converges to zero.

One may also consider only radio measurements with strong received signal strength indication, since those samples are physically close to radio node, and the most indicative of the radio node location. Additionally, radio measurements with location reference whose uncertainty does not exceed predefined threshold should be used, in order to reduce number of measurements with excessively large location error.

Yet another consideration is that location references collected within one user track are highly correlated during the dead-reckoning periods, this breaks the assumption that location error of radio measurements has even distribution. Because of this, only one radio measurement from each of the dead-reckoning segments of the track should be used. This can be done by splitting the track into segments at the times when GNSS is available. Thus, the following criteria for the radio measurements selection are applied:

- minimum required received signal strength of the radio measurement,
- maximum allowed uncertainty indication of radio measurement location,
- minimum number of radio measurements required to estimate location of radio node.
- only one radio sample per dead-reckoning segment, per sample

After measurements are selected based on the criteria above, radio node location is estimated as the mean of the locations of all the selected radio measurements. Different threshold values for the above requirements are tested and the results are presented in Section 4.

4. Experimental setup and results

Real data was used for experiments. GNSS, inertial and radio data was collected with an android device by one of the authors during daily commutes. Data collection application ran in background without any user input, android device was kept in the backpack or jacket pocket most of the time. In total 63 tracks were collected nearby and inside the test area, Technopolis office building in Tampere, and were further used in the experiments. GNSS and inertial sensor data was used to estimate locations throughout the tracks using the Kalman Filter based method outlined in Section 2, estimated tracks are visualized on the figure 1.

Estimated locations from the tracks were then used as the reference locations for Wi-Fi measurements collected throughout the track. Wi-Fi measurements were then aggregated and Wi-Fi nodes' locations were estimated based on the method outlined in Section 3.

Average error between true and estimated Wi-Fi node locations for different measurement selection criteria is visualized on the figure 2. Three axes of the plot represent three selection criteria: minimum Received Signal Strength, maximum location variance, minimum measurement count, while color coding indicates the average radio node localization error for different criteria combinations.

The minimum average error of 16.5 meters is achieved when estimation process has the following measurement selection criteria: minimum RSS for radio measurement is -65 dBm, maximum variance for measurement location reference is 1000 m, minimum number of radio measurement per Wi-Fi radio node is 10 or 20. It can be seen that selecting radio measurements with relatively high received signal strength and low location variance result in more accurate localization of radio nodes. This is because measurements with high received signal strength are close to the Wi-Fi access point, and hence better represent location of the access point. And requirement for low measurement location variance reduces number of measurements

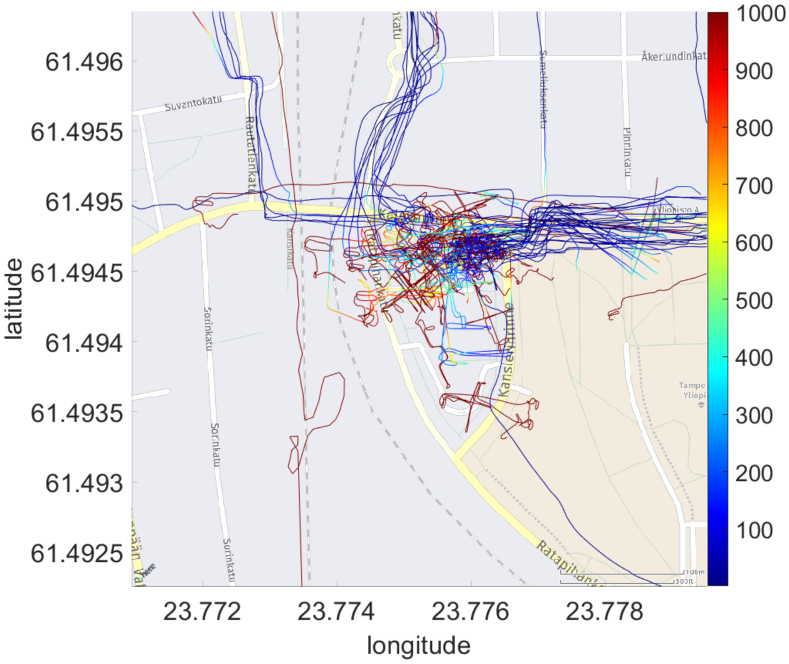

Figure 1: Tracks estimated based on Kalman Filter

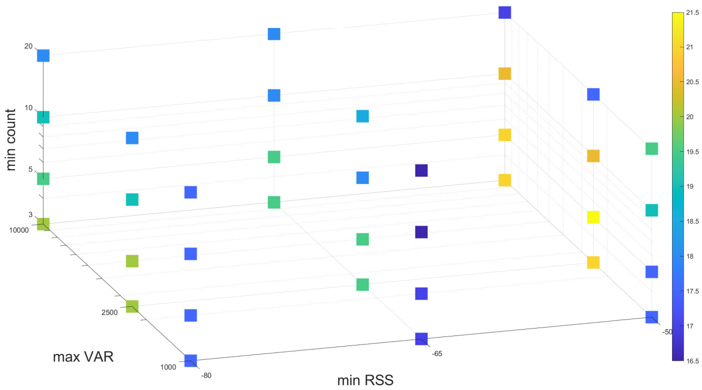

Figure 2: Average Wi-Fi Location Estimation error

with large location error. Estimated Wi-Fi nodes' locations with corresponding actual Wi-Fi nodes' locations and error vectors are visualized on the figure 3, with blue circles indicating true Wi-Fi nodes' locations, and blue lines connecting corresponding true and estimated Wi-Fi nodes' locations.

Wi-Fi nodes' locations were also estimated based on outdoor radio measurements, i.e. referenced with pure GNSS fixes. Estimated Wi-Fi nodes' locations are visualized on figure 4, the

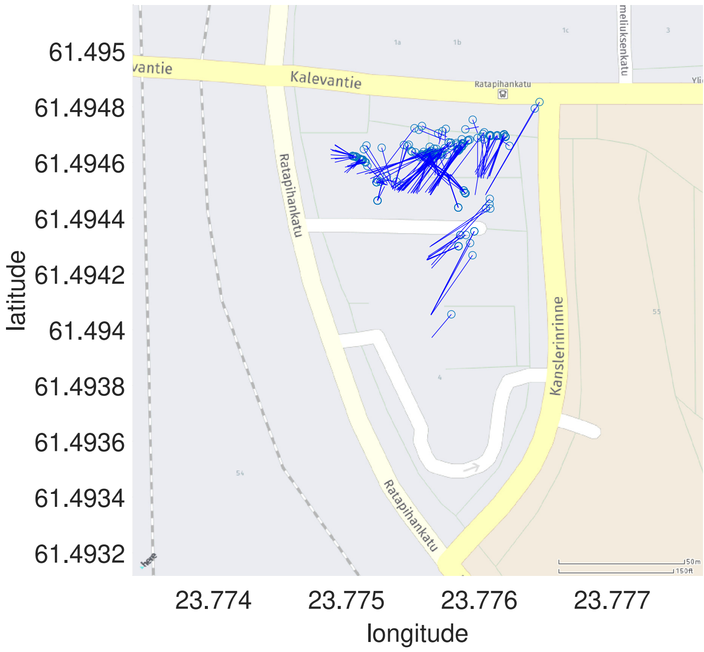

Figure 3: Wi-Fi node locations estimated based on GNSS and inertial sensor data

average localization error is 33 meters. Wi-Fi nodes' locations error statistics for estimation based on GNSS and inertial sensor data, as well as based on pure GNSS data are summarized in the table 1.

Table 1
Wi-Fi node location error

Data source	Mean	CEP68	CEP95
GNSS and IMU	16.5	19.3	32.6
GNSS	33.6	35.6	77.1

It is clear that indoor tracks estimated based on combination of GNSS and inertial sensor data do indeed provide more information and improve accuracy of Wi-Fi nodes' location estimation, compared to estimation based on GNSS referenced data.

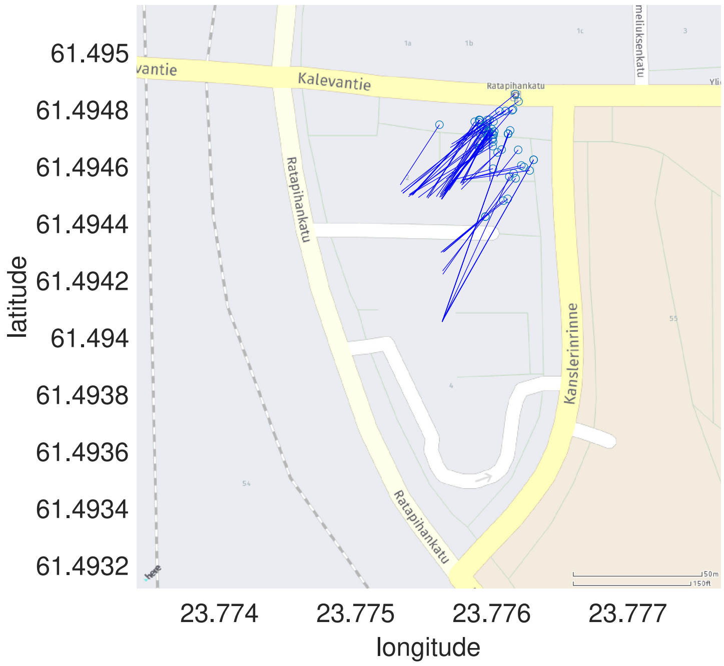

Figure 4: Wi-Fi node locations estimated based on GNSS data

5. Conclusion

Based on the presented results in can be concluded that augmenting GNSS with inertial sensor data provides additional information for Wi-Fi nodes' location estimation indoors even with simplest dead-reckoning approaches. The outlined requirements, such as high measurement signal strength, low measurement location variance, as well as sufficient number of uncorrelated measurements per access point, should be taken into account when aggregating and using large amount of user tracks for estimating locations of Wi-Fi nodes.

In the future, proposed approaches can be extended with more complex pedestrian dead reckoning methods, that, for example, estimate orientation of the device with respect to the user and use magnetometer data for more accurate tracking of user heading. Additionally, use of prior information about locations of radio nodes, e.g. in which building they are located, can be studied in the future.

References

[1] V. Honkavirta, T. Perala, S. Ali-Loytty, R. Piche, A comparative survey of wlan location fingerprinting methods, in: 2009 6th Workshop on Positioning, Navigation and Communication, 2009, pp. 243–251. doi:10.1109/WPNC.2009.4907834.

[2] L. Koski, T. Perälä, R. Piché, Indoor positioning using wlan coverage area estimates, in:

2010 International Conference on Indoor Positioning and Indoor Navigation, 2010, pp. 1–7. doi:10.1109/IPIN.2010.5648284.
[3] H. Nurminen, J. Talvitie, S. Ali-Löytty, P. Müller, E.-S. Lohan, R. Piché, M. Renfors, Statistical path loss parameter estimation and positioning using rss measurements in indoor wireless networks, in: 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2012, pp. 1–9. doi:10.1109/IPIN.2012.6418856.
[4] M. Raitoharju, T. Fadjukoff, S. Ali-Löytty, R. Piché, Using unlocated fingerprints in generation of wlan maps for indoor positioning, in: Proceedings of the 2012 IEEE/ION Position, Location and Navigation Symposium, 2012, pp. 576–583. doi:10.1109/PLANS.2012.6236930.
[5] J. Talvitie, M. Renfors, E. S. Lohan, Distance-based interpolation and extrapolation methods for rss-based localization with indoor wireless signals, IEEE Transactions on Vehicular Technology 64 (2015) 1340–1353. doi:10.1109/TVT.2015.2397598.
[6] P. Ivanov, M. Raitoharju, R. Piché, Kalman-type filters and smoothers for pedestrian dead reckoning, in: 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2018, pp. 206–212. doi:10.1109/IPIN.2018.8533753.