HOSTED BY

ELSEVIER

CrossMark

Available online at www.sciencedirect.com

ScienceDirect

ICT Express 1 (2015) 82–85

www.elsevier.com/locate/icte

An adaptive hybrid filter for practical WiFi-based positioning systems

Namjun Park, Sukhoon Jung, Dongsoo Han*

Department of Computer Science, KAIST, Daejeon, Republic of Korea

Received 23 January 2015; accepted 21 February 2015
Available online 22 October 2015

Abstract

This paper proposes an adaptive hybrid filter for WiFi-based indoor positioning systems. The hybrid filter adopts the notion of particle filters within the prediction framework of the basic Kalman filter. Restricting the predicts of a moving object to a small number of particles on a way network, and replacing the Kalman gain with a dynamic weighting scheme are the key features of the hybrid filter. The adaptive hybrid filter significantly outperformed the basic Kalman filter, and a particle filter in the performance evaluation at three test places: a Library and N5 building, KAIST, Daejeon, and an E-mart mall, Seoul.

Keywords: Indoor positioning system; Kalman filter; Adaptive hybrid filter; WiFi fingerprint; Particle filter

1. Introduction

In WiFi-based localization, the estimated location is not always accurate and it frequently oscillates even when a user stays at a fixed location. Thus, displaying the location of the user in a stable manner is one of the most challenging issues of WiFi-based indoor positioning systems. In particular, in the single time location estimation of non-moving objects, it is very difficult to cope with this accuracy fluctuation problem without the help of additional sensors such as a gyroscope, a barometer, a compass, and a 3-axis accelerometer. However, in the case of navigation or real-time tracking, we can improve or stabilize the current location estimation to some degree by referring to previous signals and location information (*i.e.*, historic data).

This paper proposes a new location filter for indoor positioning systems. Since the new filter operates in the framework basic Kalman filter (BKF) [1], and it incorporates the notion of the particles filters into the filter, we named it an adaptive hybrid filter (AHF). Like BKF, AHF does not require any additional information from sensors like a gyroscope, a barometer, a compass, or a 3-axis accelerometer. However, when necessary it uses additional information from the sensors.

When we compared the accuracies of the BKF, AHF, and a particle filter measured at a library, N5 building, KAIST, Daejeon, Korea, and an E-mart discount store, Seongsu, Seoul, a significant accuracy improvement was achieved by AHF. At a library, KAIST, around 18.0%, at N5 building, KAIST, 29%, and at an E-mart discount store, around 25.0% accuracy improvements were achieved, respectively. When we compared the accuracy of AHF with that of the particle filter, the AHF showed significantly better accuracy improvement than the particle filter while it showed a greatly improved performance in processing time compared with the particle filter. When we applied the AHF and integrated it with "myCoex", indoor navigation system, which is known as the first full-fledged commercialized indoor navigation system [2], the effect of using the AHF was apparent in improving the accuracy and the stability of location estimation.

2. Adaptive hybrid filter

2.1. State model

For a clearer understanding of the AHF, we contrast the state models of the AHF with that of BKF. The state model represents an instance of a target object at a certain time. In BKF, the state model is specified using the location and the velocity vector; that is, the state instance at time k, x_k is represented by $[C_k^x, C_k^y, V_k^x, V_k^y]^T$, where $C_k^x C_k^y$ are

* Corresponding author.
E-mail addresses: njpark@kaist.ac.kr (N. Park), sh.jung@kaist.ac.kr (S. Jung), dshan@kaist.ac.kr (D. Han).

Peer review under responsibility of The Korean Institute of Communications Information Sciences.

http://dx.doi.org/10.1016/j.icte.2015.09.008

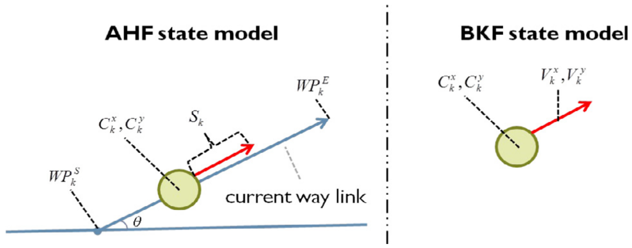

Fig. 1. State models of BKF and AHF.

coordinates of x, y at time k, and $V_k^x V_k^y$ are the velocities at time k [3].

The state model of BKF has been slightly changed in AHF. The state model of AHF consists of a location vector, speed, and way link; that is, the state instance at time k, x_k is represented by $[C_k^x, C_k^y, S_K, WP_k^S, WP_k^E]^T$, where S_K is the speed, and WP_k^S, WP_k^E respectively, are the start and the end points of a way link corresponding to an edge of a way network. In the model, the speed and the way link substitute for the velocity vectors of BKF's state model. Fig. 1 shows the state models of AHF and BKF.

2.2. Adaptive hybrid filter

Based on the state models defined above, we can describe the relation between the state instances x_k, at time k, and x_{k-1} at time $k-1$. In BKF, the relation between the states at time k and $k-1$ is defined by:

$$C_k^x = C_{k-1}^x + \delta T \cdot V_{k-1}^x,$$
$$C_k^y = C_{k-1}^y + \delta T \cdot V_{k-1}^y.$$

On the other hand, in AHF, the relation is defined by:

$$C_k^x = C_{k-1}^x + \delta T \cdot S_{k-1} \cdot \cos\theta,$$
$$C_k^y = C_{k-1}^y + \delta T \cdot S_{k-1} \cdot \sin\theta,$$

where, θ is the angle of the way link and the base line. The base line is shared by all the way links. Since there are two directions on a straight line, θ can have two possible values on the straight line: θ and $\theta + \pi$. At a perpendicular four-way intersection, θ can have four possible values: $\theta, \theta + \pi/2,\ \theta + \pi,\ \theta + 3\pi/2$.

This means that for an instant on a straight line, we assume there are two possible candidates for predictions: forward and backward directions. For an instant on a four-way intersection, we assume that there are four possible candidates for predictions. Among the candidates, the closest candidate to the measurement is chosen as the final prediction. As long as the angle of the way links connected to the intersections is known, the number and the angle of the way links do not matter in AHF. Note that we can obtain the angle of each way link once the way network is derived from a map. The prediction model of AHF is described by:

$$\begin{bmatrix} C_k^x \\ C_k^y \\ S_k^x \end{bmatrix} = \begin{bmatrix} 1 & 0 & \delta T \cdot \cos\theta \\ 0 & 1 & \delta T \cdot \sin\theta \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} C_{k-1}^x \\ C_{k-1}^y \\ S_{k-1}^x \end{bmatrix} + \begin{bmatrix} w_k^{C^x} \\ w_k^{C^y} \\ w_k^{S^x} \end{bmatrix}$$

where, w_k is the process noises $w_k \sim N(0, Q_k)$, and Q_k is the process error covariance. In the observation model of AHF, the observation z_k is defined by:

$$\begin{bmatrix} z_k^x \\ z_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} C_k^x \\ C_k^y \\ S_k^x \end{bmatrix} + \begin{bmatrix} v_k^x \\ v_k^y \end{bmatrix}$$

where, v_k is the observation noise $v_k \sim N(0, R_k)$, and R_k is observation error covariance.

Meanwhile, the BKF update is performed using Kalman gain, which is obtained from an error covariance matrix. Kalman gain is used for assigning weights for the combination of a prediction and a measurement. If the measured location is unreliable, it assigns a higher weight to the predicted location. If the measured location is reliable, it assigns a higher weight to the measured location. We leave the details on how to compute the error covariance matrix and Kalman gain to [1].

AHF does not use Kalman gain in the update because Kalman gain usually converges into a specific value. As a result, Kalman gain has limitations in reflecting the accuracies of WiFi-based localization that change dynamically. In AHF, instead of building an error covariance matrix, the accuracy at each location is computed, and then it computes the relative error level of each location. Best Candidate Set (BCS) method [4] was used for the error estimation. In BCS, the error is computed by the distances between the nearest neighbor and the remaining neighbors estimated using a method similar to kNN method. After the relative error level is determined, the weights for a prediction and a measurement are defined by:

$$N_k = \frac{1}{\frac{1}{k-1}\sum_{i=1}^{k-1} err_i^e} + \frac{1}{err_k^e} \quad w_k^p = \frac{1}{N_k} \cdot \frac{1}{\frac{1}{k-1}\sum_{i=1}^{k-1} err_i^e}$$
$$w_k^m = \frac{1}{N_k} \cdot \frac{1}{err_k^e},$$

where x_k^p, y_k^p are the coordinates of a prediction, which are the results of a prediction phase, and x_k^m, y_k^m are coordinates of an estimated location into a real number in the range of 0–1. The weight increases as the average of estimated errors decreases. Once the weight is computed, the filter combines the predictions and measurements by:

$$x_k = w_k^p \cdot x_k^p + w_k^m \cdot x_k^m$$
$$y_k = w_k^p \cdot y_k^p + w_k^m \cdot y_k^m,$$

where, x_k^p, y_k^p are the coordinates of a prediction, which are the results of a prediction phase, and x_k^m, y_k^m are coordinates of an estimated location.

3. Experimental results

3.1. Experiment setup

In order to evaluate the validity of AHF for indoor navigation, we collected three datasets: one from the 4th floor of a KAIST library, one from the 2nd floor of N5 building, KAIST, Daejeon, and one from the 1st floor of E-mart at Seongsu, Seoul, Korea. The 4th floor of KAIST library is an open space of 2232 m^2, and the space is divided by 67 bookshelves, making the way networks complicated. As the number of APs pre-installed on the floor was too small to construct a WLAN radio map, we installed 18 APs additionally. The learning data was collected at 557 points, and 20 fingerprints were collected at each point. For the test data, 20 traces were collected, and each of the traces included 174 measure points. The evaluation is also conducted in a long hallway of the 2nd floor of N5 building, KAIST, with a size of 7553 m^2. The learning data was collected at 74 measure points in the same manner as performed at the KAIST library.

E-mart is one of the biggest discount stores with 200 chains in Korea, and E-mart located at Seongsu is the headquarters and main store of the chain. The data was collected on the 1st floor, which was 8800 m^2. E-mart is an open space, and the area is divided by dozens of shelves. The size of the area is much larger than that of the KAIST library and the AP density was sparser like the KAIST library. Thus, 40 APs were additionally installed for the experiment. The learning data was collected at 725 points, and 14,500 fingerprints were collected in total. For the test data, like the case of the KAIST library and N5 Building, 20 traces were collected, and each trace included 188 measure points.

3.2. Evaluation results

We compared the accuracy improvement achieved by AHF, a particle filter, and BKF respectively at the KAIST library, N5 building, and E-mart. A weighted k-NN algorithm was used to implement a positioning system to evaluate the performance of the methods. The performance was evaluated after integrating the BKF, AHF, and a particle filter with the positioning system. The particle filter performed its prediction with 5000 particles. In the particle filter, we confined the location of the particles to appear only on the way network. Since there are many different ways of assigning weights for AHF and particle filters, we used a uniform value in assigning weights to particles for a fair comparison. We prepared 10 traces and the results are obtained by computing the average of the 10 traces.

As shown in Table 1, AHF showed the best accuracy among the three methods both at the KAIST library and the E-mart. At the KAIST library, AHF achieved an accuracy improvement of 18.0% compared with the accuracy measured without filtering (from 3.48 to 2.85 m in the average error distance), whereas BKF achieved an accuracy improvement of only 7.4% and the particle filter 12.0%. At the KAIST N5 building, as much as 28.9% accuracy improvement was made by AHF (from 4.60 to 3.27 m), whereas BKF achieved only an accuracy improvement of 2.5%, and the particle filter, 13.9%. At the E-mart, as much as 25.0% accuracy improvement was made by AHF (from 4.88 to 3.66 m), whereas BKF achieved only an accuracy improvement of 15.0%, and the particle filter, 23.4%.

The processing time of particle filter was about 80 times slower than that of AHF. If we use the less number of particles, we could further reduce the processing time of the particle filter. But instead, the accuracy was downed. For example, when we used 1000 particles, we could reduce the processing time of particle filter by 5 times. But the accuracy was downed about 7–8% in both of the cases. On the other hand, when we increased the number of particles to 10,000, only the processing time greatly increased without any further improvement of accuracy.

Table 1
The summary of evaluation for BKF, AHF, and a particle filter at KAIST library, N5 building, Daejeon and E-mart, Seongsu, Seoul.

Testbed	Methods	Average distance error (m)	Improvement rate	Processing time
KAIST Library	No filtering	3.48	0%	0 μs
	BKF	3.22	7.4%	21 μs
	AHF	2.85	18.0%	30 μs
	Particle filter	3.06	12.0%	2322 μs
KAIST N5 building	No filtering	4.60	0%	0 s
	BKF	4.48	2.6%	15 μs
	AHF	3.27	28.9%	33 μs
	Particle filter	3.96	13.9%	1588 μs
E-mart	No filtering	4.88	0%	0 s
	BKF	4.15	15.0%	17 μs
	AHF	3.66	25.0%	21 μs
	Particle filter	3.74	23.4%	2376 μs

The reason that we could achieve more improvement at KAIST N5 building and E-mart than at KAIST is because the lengths of straight lines at KAIST N5 building and E-mart were usually longer than those at the KAIST library. Usually, we can expect a greater filtering effect on straight lines than at corners or intersections.

4. Conclusion

In this paper, we proposed an adaptive hybrid filter (AHF) for indoor navigation that was newly developed by extending the conventional BKF scheme. The proposed AHF has achieved a considerable improvement in the accuracy for the three datasets of the KAIST Library, N5 building, and E-mart. This accuracy improvement is mainly due to the restriction of the movement of the moving target object to the way network as well as the dynamic weighting scheme based on error estimation. We can further improve the accuracy if we develop a more advanced and reliable error estimation technique, which is currently an open problem. Furthermore, incorporating sensing data from various sensors in a smartphone such as 3-axis accelerometer and gyroscope into the AHF would be another source for more accuracy improvement.

Acknowledgments

"This work was supported by the Center for Integrated Smart Sensors funded by the Ministry of Science, ICT

& Future Planning as Global Frontier Project" (CISS-2012M3A6A6054195).

References

[1] R.E. Kalman, A new approach to linear filtering and prediction problems, J. Basic Eng. 82 (1) (1960) 35–45.

[2] D. Han, S. Jung, M. Lee, G. Yoon, Building a practical Wi-Fi-based indoor navigation system, IEEE Pervasive Comput. 13 (2) (2014) 72–79.

[3] A. Bekkali, H. Sanson, M. Matsumoto, RFID indoor positioning based on probabilistic RFID map and Kalman filtering, in: WiMOB, 2007.

[4] H. Lemelson, M.B. Kjærgaard, R. Hansen, T. King, Error estimation for indoor 802.11 location fingerprinting, Lecture Notes in Comput. Sci. 5561 (2009) 138–155.