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A sensor fusion method for Wi-Fi-based indoor positioning☆

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Abstract

This paper presents a sensor fusion method for a Wi-Fi-based indoor positioning system, named the KAist Indoor LOcating System (KAILOS), which was developed to realize a global indoor positioning system (GIPS) that utilizes crowd-sourced fingerprints. KAILOS supports the deployment of indoor positioning systems in buildings by collecting indoor maps and fingerprint DBs of buildings for the GIPS. Thereby, KAILOS provides a method based on sensor fusion for volunteers to develop indoor positioning systems for their buildings. KAILOS has been made available online for public use. In addition, various location-based applications can also be developed using KAILOS.

1. Introduction

The KAist Indoor LOcating System (KAILOS) has various unique features that distinguish it from other indoor positioning systems. One of these features is the positioning algorithm it employs to provide an accurate positioning service [1]. An extended Viterbi algorithm was developed to track a user by using historical data comprising Wi-Fi fingerprints, magnetic fingerprints, and sensing data from inertial sensors such as a three-axis accelerometer, a gyroscope, a compass, and a barometer.

The extended Viterbi algorithm integrates the readings from the various smartphone sensors into its probabilistic framework for a more accurate positioning. Moreover, the algorithm uses a novel Wi-Fi fingerprinting scheme, named the Signal Fluctuation Matrix (SFM), to extract optimized performance from sparsely collected fingerprint data.

In this paper, we briefly introduce the process of deploying an indoor positioning system using KAILOS. This system provides methods, tools, and interfaces to register indoor maps, construct radio maps, visualize signal distributions, and more. Among the many methods and tools of KAILOS, we focus especially on its sensor fusion method, which is designed to incorporate various sensors, and the SFM method to further improve the performance of Wi-Fi based indoor positioning. The techniques have been integrated in the Viterbi tracking framework, the construction of which is based on a Hidden Markov Model (HMM).

The effectiveness of KAILOS was evaluated by integrating the Wi-Fi and sensor signals within the extended Viterbi tracking algorithm. This was found to greatly improve the performance of indoor positioning in experiments performed using the seventh floor of the N1 building of KAIST as the experimental setting.

2. KAILOS

2.1. Tools to deploy an indoor positioning system

KAILOS contains various methods and tools to enable volunteers to register indoor and radio maps of any building. These tools are available on the KAILOS web site (http://kailos.io). Selected web pages depicting the KAILOS user interface are shown in Fig. 1. Once the indoor map of a building is registered, the Wi-Fi and magnetic fingerprints of the building can be collected and input into KAILOS by using a point-by-point manual calibration [2], a walking survey [1], or a reference-free calibration [3].

The ability to construct radio maps is another feature distinguishing KAILOS from other indoor positioning systems. It supports all kinds of radio map construction methods including a novel unsupervised learning-based reference-free calibration method [3]. The method automatically labels the

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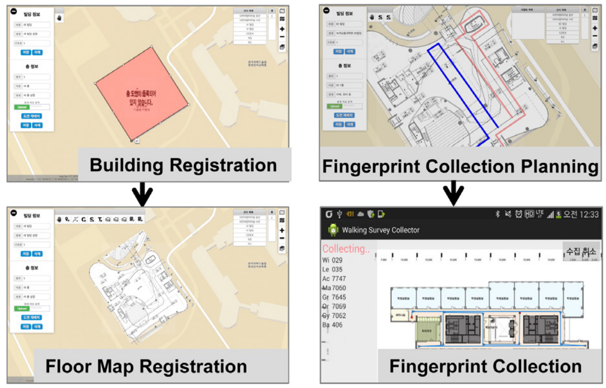


(a) Indoor map construction. (b) Fingerprint map construction.

Fig. 1. Deployment process of indoor positioning system.

locations of crowd-sourced fingerprints that are collected without location information. Because the reference-free calibration method does not require any explicit effort from participants or additional information from GPS and inertial sensors for calibration purposes, it can be effectively used for constructing radio maps of buildings all over the world.

Volunteers who want to deploy indoor positioning systems in their buildings can choose from one of three calibration methods considering the construction cost and accuracy of the system. The point-by-point manual calibration method can be used to implement a highly accurate positioning system for a particular indoor space such as exhibition and convention centers, discount stores, and indoor shopping malls. Despite the cost of the reference-free calibration method being almost zero, it may result in a less accurate positioning system. This method is either suitable for large-scale or remote buildings of which the crowd-sourced fingerprints are available.

2.2. Probabilistic framework for user-tracking and sensor fusion

The accuracy of positioning algorithms changes the way the available data, such as radio maps [4], inertial sensor readings, the results of trajectory-tracking [5], and map matching, is incorporated. The fusion of these diverse types of data is also one of the key issues that need to be addressed [6]. KAILOS overcomes this problem in the probabilistic framework of the extended Viterbi algorithm on HMM, which was used to model an indoor area. In KAILOS, the topology of the HMM is automatically constructed based on the structures of a building, such as its walls and barriers, which are specified on the indoor map. This topology is used to estimate user movements in the particular indoor space, and to perform map matching.

Meanwhile, sensor data is categorized into two types: the first type is used to estimate an absolute position, and the second to estimate changes in the relative positions of users. The absolute positions of users are estimated using Wi-Fi and magnetic fingerprints, which are used to calculate the emission probabilities of the HMM. The transition probabilities of the HMM are calculated during run-time using inertial sensor readings to estimate the change in the relative position. The emission and transition probabilities of the HMM are then used to fuse the two types of sensor data in the probabilistic framework of the HMM to provide accurate trajectory tracking and user positioning.

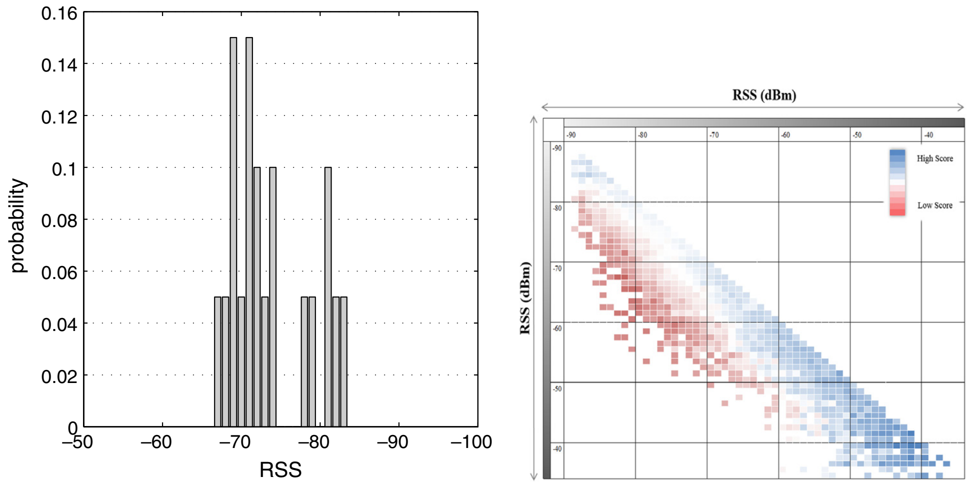
2.2.1. Signal fluctuation matrix

Traditionally, radio maps have represented the characteristics of signals from the respective APs at a particular location in the form of a histogram, Gaussian distribution, or lognormal distribution of the Received Signal Strength (RSS) [6]. These strategies typically require a large number of samples at each location in order to precisely represent the characteristics of the signals with the RSS distributions. Here, we propose a new method to represent the characteristics of fingerprints using an SFM. This method mitigates the need for a large number of samples that cannot be satisfied by crowd-sourced fingerprints. The method ignores the differences between the RSS distribution patterns for each location and AP, and considers the probability of fluctuation between two RSS values at a location. The universal patterns of the fluctuations are represented in a two-dimensional SFM. Because the fluctuation in a particular pair of RSS values can be observed at any location, a reliable SFM can be obtained even if only a small number of samples are available at each location.

Fig. 2 illustrates the difference between radio maps represented by an SFM and a normal histogram. We collected 20 samples at each location in our experimental setting on the seventh floor of the N1 building of KAIST for the experiment. As shown in Fig. 2, the histogram that was constructed from only 20 samples was unreliable because many bins were empty. However, the SFM could overcome the lack of training samples and proceeded to fill all of the cells in the matrix with frequency values. An SFM can be regarded as a universal histogram of RSS values irrespective of locations and APs. The SFM calculates the probability of observing an online RSS i of an AP at a location l as a log-odd probability,

$$P\,(i|l) = \log\left(\frac{P(i,\ j)}{P\,(i)\ P(j)}\right), \tag{1}$$

where j is the mean RSS of the AP trained at l, $P(i,\ j)$ is the observed fluctuation probability of an RSS pair $(i,\ j)$ stored in



(a) Histogram. (b) SFM.

Fig. 2. Comparison of SFM- and histogram-based Wi-Fi fingerprints.

the SFM, and $P(i)\,P(j)$ is the expected fluctuation probability of the pair [7]. The emission probability $P(o|l)$ of an online Wi-Fi fingerprint o is simply calculated by $\prod_{i\in o} P(i|l)$.

Magnetic fingerprints can also be represented in a structure similar to that of an SFM. However, we use a Gaussian distribution for the magnetic fingerprints because the fluctuation of the magnetic norm at a location is not as severe as that of Wi-Fi signals. When a magnetic norm m is measured along with o in the online phase, the emission probability of the measurements $P(o, m|l)$ is simply calculated by $P(o|l) \times P(m|l)$.

2.2.2. *Fusion of inertial sensor data*

The Viterbi algorithm can use the calculated emission probabilities to track a user if the transition probabilities are provided by the inertial sensors in a device. The inertial sensors in a smartphone usually provide a deterministic relative position change with considerable errors in distance and heading calculations. Hence, the deterministic results should be converted to a probabilistic distribution at each location, and the errors should be compensated to some extent. The extended Viterbi tracking algorithm addresses these problems by accumulating the distributions of errors in the distance and heading calculations. The errors are estimated under the assumption that the tracking results fairly closely approximate the correct answers.

Fig. 3 illustrates the process by which the transition probability is calculated. Suppose a trajectory tracking from time t_0 to t_3 has been performed as shown in the figure. The bold arrows depict the tracking results, whereas the dotted arrows denote the distance and heading information provided by the inertial sensors at each point in time. At time t_0, the probability distribution of the transitions out of the first location is depicted by a gray circle, of which the center is indicated by the inertial sensor readings. However, a mismatch can happen between the inertial sensor readings and the tracking results. The error resulting from this mismatch should be attributed to the inertial sensors, and should be compensated for in the calculation of the next transition probabilities. As time proceeds, the errors in the distance and heading calculations are gradually mitigated,

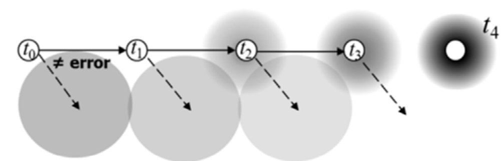


Fig. 3. Transition probability calculation and error compensation.

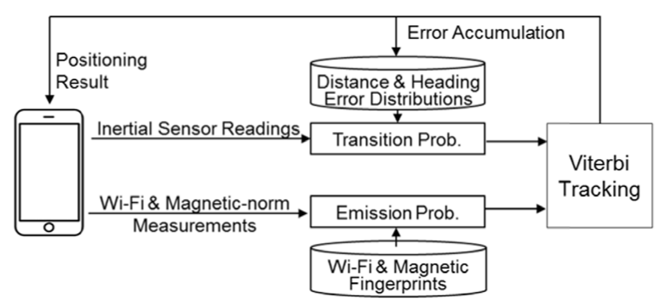


Fig. 4. Extended Viterbi algorithm for sensor fusion.

as shown in the figure. As a result, at time t_4, the tracking algorithm can utilize the corrected probability distributions depicted by the dark circle.

Fig. 4 presents an overview of the KAILOS positioning framework. The measured Wi-Fi signals and magnetic-norms are used to compute the emission probabilities and the sensor readings are used to compute the transition probabilities. The Viterbi tracking algorithm incorporates the various probabilities to estimate the final location.

3. Evaluation

We performed experiments to confirm the effectiveness of the methods. An experiment was performed by using the seventh floor of the N1 building of KAIST as our experimental setting to compare the performance of the Euclidean, Gaussian, histogram, and SFM methods. Fig. 5 shows the results of the comparison in the form of a CDF graph. As shown in the graph, the SFM-based method outperformed the existing positioning

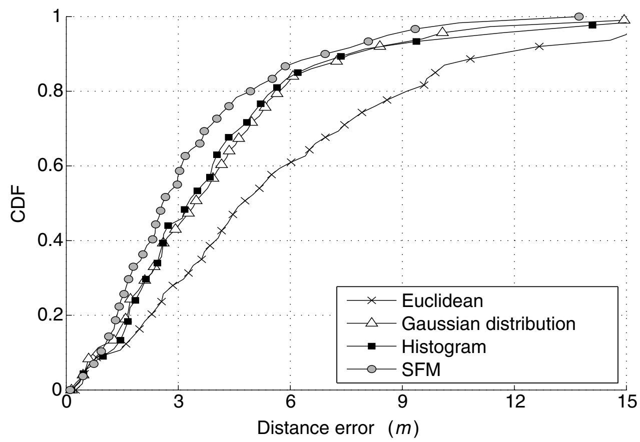


Fig. 5. Cumulative Distribution Function (CDF) of positioning errors of probabilistic positioning algorithms using various fingerprint types.

methods, indicating that SFM is able to effectively improve the accuracy of positioning.

An additional experiment was performed to test the effectiveness of sensor fusion on the same floor of the same building. When the sensor fusion method was used for positioning, the accuracy was improved by more than 100%. The average error in the distance was improved from 2 to 3 m using only Wi-Fi signals to less than 1 m using various sensors. The incorporation of the magnetometer was the most effective in improving the accuracy once the particles of the particle filter were merged into a group. On the other hand, the Wi-Fi signals were the most effective in finding the initial location. The inertial sensors were effective for detecting a change in direction.

4. Conclusion

This paper presents two techniques: SFM and sensor fusion, both of which were shown to be highly effective in improving the positioning accuracy of Wi-Fi-based indoor positioning systems. The techniques are now available in KAILOS, which is a crowdsourcing-based global indoor positioning system that we have made publicly available on the Internet. The greater the number of users who deploy indoor positioning systems on KAILOS, the sooner a global indoor positioning system could be realized.

Acknowledgments

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