KAILOS: KAIST Indoor Locating System

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I. ABSTRACT

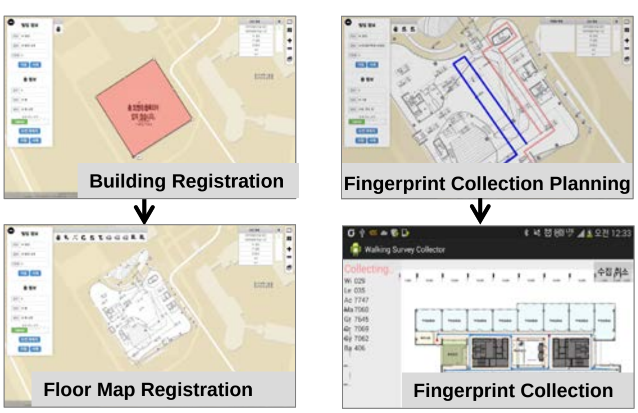
This paper presents KAist Indoor LOcating System (KAILOS), which aims to provide a global indoor positioning service through crowdsourcing. KAILOS provides methods and tools for volunteers to develop indoor positioning systems for their buildings. Anyone can deploy indoor positioning systems in their buildings on KAILOS. In addition, various location based applications can also be developed on KAILOS using APIs provided by the system.

KAILOS has many unique features distinguishing it form other indoor positioning systems. Positioning algorithm is one of such features. KAILOS employs advanced positioning algorithms to provide accurate positioning service. For example, an extended Viterbi algorithm was developed for the tracking of a user using the historical data of Wi-Fi fingerprints, magnetic fingerprints, and sensing data from inertial sensors such as a 3- axis accelerometer, a gyroscope, a compass, and a barometer. The extended Viterbi algorithm successfully integrates the readings from various smartphone sensors in its probabilistic framework. In addition, a novel Wi-Fi fingerprinting scheme, named Signal Fluctuation matrix (SFM), was developed to extract an optimized performance from sparsely collected fingerprint data.

A. *Tools to deploy an indoor positioning system*

KAILOS provides tools and interfaces for volunteers to register indoor maps and fingerprint DB of any building. They are available at KAILOS web site (http://kailos.io) as shown in Fig. 1. Once the indoor map of a building is registered, Wi-Fi and magnetic fingerprints of the building can be contributed to KAILOS through either point-by-point manual calibration, walking survey [1] or reference-free calibration [2].

Fingerprint DB construction is another feature distinguishing KAILOS from other indoor positioning systems. It attempts to support all kinds of fingerprint DB construction methods including a novel unsupervised learning-based reference-free calibration method [2]. The method automatically labels locations of crowdsourced fingerprints that are collected without location information. Since the reference-free calibration method does not require any explicit efforts from participants or additional information from GPS and inertial sensors for the calibration, it can be effectively used for constructing radio maps for buildings all over the world.



(a) Indoor map construction. (b) Fingerprint map construction.
Fig. 1. Process of indoor positioning system deployment.

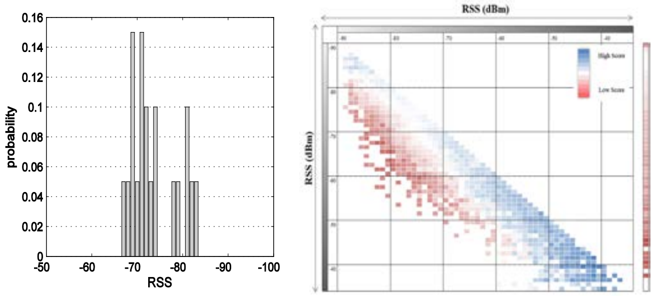
Volunteers who want to deploy indoor positioning systems in their buildings can choose one of the three calibration methods considering the construction cost and accuracy of the system. The point-by-point manual calibration method can be used to construct a highly accurate positioning system for a particular indoor space such as exhibition and convention centers, discount stores, indoor shopping malls, and others. On the other hand, though the cost of the reference-free calibration is almost zero, it may results in a less accurate positioning system. Thus, this method would be effectively used for large-scale buildings or buildings where crowdsourced fingerprints are available.

B. *Probabilistic framework for user-tracking & sensor fusion*

The accuracy of positioning algorithms changes by the way of incorporating available data, such as fingerprint DB, inertial sensor readings, and results of trajectory-tracking and map-matching. The fusion of these data is also one of the key issues. KAILOS addresses these problems in the probabilistic framework of the extended Viterbi algorithm on Hidden Markov Model (HMM) used to model an indoor area. In KAILOS, the topology of an HMM is automatically constructed using the structures of a building, such as walls and barriers, specified in an indoor map. This topology is used to speculate user movements in an indoor space, and perform a map-matching.

Meanwhile, we categorize sensor data into two types; one to reflect absolute positions, and the other to reflect relative position changes of users. Wi-Fi and magnetic fingerprints have been used to indicate absolute position of a user. They are used to calculate the emission probabilities of an HMM. The transition probabilities of the HMM are calculated in run-time using inertial sensor readings indicating relative position changes. Using the emission and transition probabilities, the two types of sensor data are fused in the probabilistic framework of HMM, which also provides accurate trajectory-tracking and positioning of a user.

1) Signal Fluctuation Matrix: Traditionally, Wi-Fi fingerprints have been constructed for each AP at each location with a histogram, Gaussian distribution, or lognormal distribution of Received Signal Strength (RSS). These strategies require a large amount of samples at each location in order to fully observe the RSS distribution phenomena. Here, we propose a new fingerprint design called SFM to mitigate the need for the large amount of samples, because not so many



(a) histogram. (b) SFM

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

samples are assumed to be available at each location in crowdsourced fingerprint datasets. The method ignores the differences of RSS distribution patterns for each locations and APs, but considers the probability of fluctuating between two RSS values at a same location. The universal patterns of the fluctuations are stored in a two-dimensional matrix called SFM. Because a fluctuation of a certain pair of RSS values can be observed from any location and AP, a reliable SFM can be obtained even if a small number of samples are available at each location.

Fig. 2 illustrates the difference of fingerprints DBs represented by SFM and normal histogram. We collected 20 samples at each location in 7th floor of 1N building, KAIST, Daejeon, for the experiment. As can be seen in Fig. 2, the histogram constructed from only 20 samples seems to be unreliable because many bins are empty. However, the SFM could address the lack of training samples; all of the cells in the matrix are filled with frequency values. SFM can be seen as a universal histogram of RSS values irrespective of locations and APs. With the SFM, the probability of observing an online RSS i of an AP at a location l is calculated as log-odd probability as follows,

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

where, j is mean RSS of the AP trained at l, $P(i,j)$ is the observed fluctuation probability of an RSS pair (i,j) stored in SFM, and $P(i)P(j)$ is the expected fluctuation probability of the pair [3]. The emission probability $P(o|l)$ of an online Wi-Fi fingerprint o is simply calculated by $\prod_{i\in o} P(i|l)$.

Fig. 3 shows comparison of positioning errors using SFM and typical fingerprint representations in the 7th floor, 1N building. As can be seen in the figure, SFM-based positioning outperformed the other conventional positioning methods.

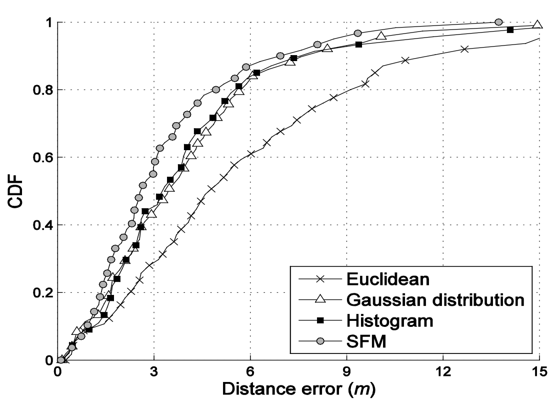


Fig. 3. The CDF of positioning errors of probabilistic positioning algorithms using various fingerprint types.

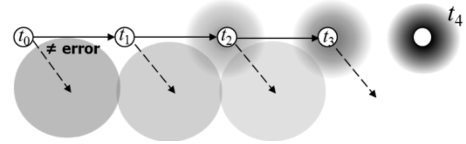


Fig. 4 Transition probability calculation and error compensation.

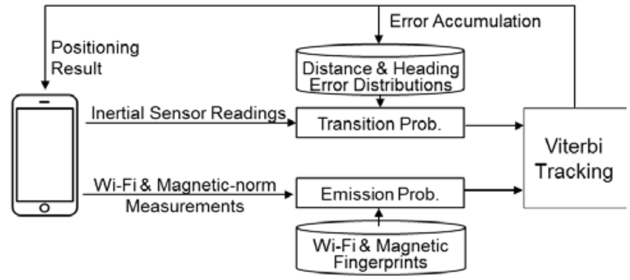


Fig. 5 Extended Viterbi algorithm for sensor fusion.

Magnetic fingerprints can also be stored in a similar structure to SFM. Nevertheless, we use Gaussian distribution for the magnetic fingerprints, because the fluctuation of the magnetic norm at a location is not so severe as 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) Fusion of inertial sensor data: With the calculated emission probabilities, the Viterbi algorithm can track a user if transition probabilities are given by inertial sensors. Inertial sensors in a smartphone usually provide deterministic relative position changes with considerable errors in distance and heading calculations. Therefore, the deterministic results should be converted to a probabilistic distribution at each location, and the errors should be compensated. 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 are fairly close to the correct answers.

Fig. 4 illustrates the process of transition probability calculation. Suppose trajectory-tracking for time t_0 to t_3 has been performed as shown in the figure. The bold arrows depict the tracking results, and dotted arrows indicate distance and heading information given by the inertial sensors at each time. At time t_0, the probability distribution of the transitions out of the first location is shown as a gray circle with the center indicated by the inertial sensor readings. However, there has been a mismatch between the inertial sensor readings and the tracking result. This mismatch is regarded as the error of inertial sensors, and compensated for the calculation of the next transition probabilities. As time goes by, the errors in distance and heading calculations are gradually mitigated as seen in the figure. As a result, at time t_4, the tracking algorithm can utilize the corrected probability distributions depicted by a dark circle. Fig. 5 is an overview of KAILOS positioning framework.

REFERENCES

[1] D. Han, S. Lee, and S. Kim, “Kailos: Kaist indoor locating system,” in *Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference on*, Oct 2014, pp. 615–619.

[2] S. Jung, B. Moon, and D. Han, “Unsupervised learning for crowdsourced indoor localization in wireless networks,” *Mobile Computing, IEEE Transactions on*, vol. PP, no. 99, pp. 1–1, 2015.

[3] A. Y. Zomaya, Handbook of nature-inspired and innovative computing: integrating classical models with emerging technologies, Springer, 2006.