

# A sensor fusion method for Wi-Fi-based indoor positioning<sup>☆</sup>

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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.

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## 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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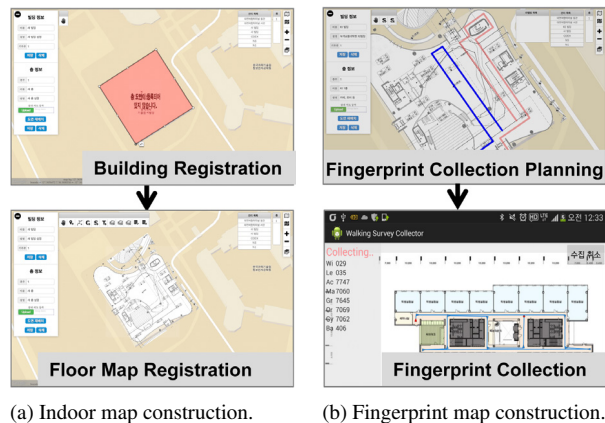


Fig. 1. Deployment process of indoor positioning system.

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,

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

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

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