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# Coursa Venue: Indoor Navigation Platform Using Fusion of Inertial Sensors with Magnetic and Radio Fingerprinting

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***Abstract*—Navigation is one of the most essential human needs. People need to know their location anywhere and everywhere, indoors and outdoors, for example for tracking children and older people who are in extreme need of care or for providing a precise indoor location of calls to 911. The latter is especially important since more than seventy percent of calls are generated indoors. Other important fields are tracking of personnel in possibly dangerous environment, LBS/LBA applications, and social networking that rely on indoor localization. Unfortunately, broadly used satellite navigation receivers work perfectly only under open sky. Operating indoors, GPS/GNSS receivers suffer from signal attenuation when satellite signals propagate through a roof and walls of a building and from the multipath due to their reflection. As a result, accurate GNSS-based position fix is almost impossible in most indoor conditions. We present Coursa Venue solution that was developed by TDK-Invensense for infrastructure-less indoor positioning on commercial smartphones. The solution consists of two major parts: cloud-based software for fingerprinting and mobile applications for Android and iOS that provide real-time blue dot positions to users. TDK-Invensense's approach to real-time indoor positioning is based on fusion of multiple technologies. Measurements from such smartphone sensors as IMU (3D accelerometer, gyroscope), a magnetic field sensor (3D magnetometer), WiFi and BLE modules are used for hybrid indoor positioning in the navigation engine. Particle filtering is used as the fusion engine. Indoor navigation software uses such technologies as PDR, geomagnetic fingerprinting, Wi-Fi/BLE fingerprinting, and, optionally, map matching. TDK-Invensense's PDR provides prediction of user relative movement regardless of orientation and misalignment of a smartphone, whereas magnetic and radio fingerprinting serves for correction of inertial sensors error. The cloud-based component can create magnetic and radio fingerprint databases using either data collected by designated surveyors who walked inside a venue by predetermined routes, or crowdsourced data from users of a real-time mobile application collected during their everyday activity. This paper discusses the architecture of the Coursa Venue solution and demonstrates its positioning results in several venues with comparison to ground truth paths to provide statistical assessment and key performance indices.**

***Keywords—inertial sensors, sensors fusion, location fingerprinting, PDR, particle filter***

## I. INTRODUCTION

Navigation is one of the most essential people's needs. People need to know their location anywhere and everywhere, for example for tracking children and older people who are in extreme need of care. Or provide a precise indoor location of calls to 112 or 911. It is especially important since more than seventy percent of calls are generated indoors [1]. Other important field is Location Based Services (LBS) and Advertising (LBA) and social networking that rely on indoor localization.

Satellite navigation revolutionary changed people's life. Modern smartphones support both operable navigation systems – GPS and GLONASS - and are ready to support Galileo and Beidou. Unfortunately, satellite navigation works perfectly only under the open sky. Operating indoors, GPS/GNSS receivers suffer from signal attenuation when satellite signals propagate through a roof and walls of a building and from the multipath due to their reflection. As a result, the position fix is almost impossible in most indoor conditions.

We present Coursa Venue solution that was developed by TDK-Invensense for infrastructure-less indoor positioning on commercial smartphones. The solution consists of two major parts: cloud-based software for fingerprinting and mobile applications for Android and iOS that deliver real-time blue dot positions to users.

Nowadays smartphones became one of the most popular devices in people's daily life, which very largely go by indoors. As stated in [1], "80 percent of smartphone usage occurs inside buildings". In addition to the GPS/GNSS receiver, smartphones are equipped with a large variety of sensors such as accelerometer, gyroscope, magnetometer, barometer, camera, microphone, touch screen, etc. It is also necessary to mention such radio communication modules as WiFi, Bluetooth including Bluetooth Low Energy (BLE), and Near Field Communication (NFC).

Recently indoor localization methods have excited big interest. Different aspects of indoor localization were analyzed in surveys [2]-[4] and in number of conference and journal publications. For example, WiFi RSSI-based localization methods were discussed in [5] and [6], geomagnetic-based localization – in [7] and [8], whereas

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concurrent use of several positioning methods - in [9] and [10]. Due to data fusion, the latter allows achieving better accuracy compared with a single positioning method. Heterogeneous data fusion is usually realized on basis of the Particle Filter (PF), which is implementation of the Bayesian filter using the sequential Monte Carlo method [11].

TDK-Invensense's approach to real-time indoor positioning is based on fusion of multiple technologies. Measurements from such smartphone sensors as Inertial Measurement Unit (IMU) comprising 3D accelerometer and gyroscope, a magnetic field sensor (3D magnetometer), WiFi and BLE modules are used for hybrid indoor positioning in the navigation engine. Particle filtering is used as the fusion engine. Indoor navigation software uses such technologies as Pedestrian Dead Reckoning (PDR), geomagnetic fingerprinting, Wi-Fi/BLE fingerprinting, and, optionally, map matching. TDK-Invensense's PDR provides prediction of user relative movement regardless of orientation and misalignment of a smartphone, whereas magnetic and radio fingerprinting serves for correction of errors of the inertial sensors.

The rest of the paper is organized as follows. In Section II we observe system architecture. Section III discusses fusion of different positioning techniques used in our hybrid solution. Section IV contains positioning results obtained in different venues. Finally, we give a conclusion in Section V.

## II. System Architecture

Coursa Venue is an indoor location platform using a mixture of positioning technologies. The goal of this platform is to enable venue-owners or service providers with tools and services to create navigation, shopping guides, location-based advertising, location-based search for venue visitors, and venue analytics.

One of the attractive technologies for indoor positioning is fingerprint-based positioning, such as WiFi fingerprinting, BLE fingerprinting, geomagnetic fingerprinting and others. Fingerprint-based approach in many cases allows to avoid deployment of special infrastructure for positioning. For WiFi-fingerprinting, it has an additional advantage of avoiding accurate radio wave propagation modelling with its challenging multipath effects in complicated indoor environment.

Fingerprint-based positioning indoors is based on comparison of measurements of some physical variables, e.g. WiFi Received Signal Strength Indicator (RSSI) measurements or magnetometer readings, in unknown position with similar measurements in known positions. The latter is known as a fingerprint database (DB) that is a key component of fingerprint-based positioning. Creating the fingerprint DB requires collecting measurements in locations inside a building separated by some distance, e.g. 1 or 2 meters, and then estimating magnetic or radio field in those positions by processing collected measurements. Traditionally, collecting WiFi RSSI or magnetic measurements are provided by systematic survey when surveyors equipped with a measurement device like a smartphone traverse predetermined routes inside a building. This is a laborious and time-consuming process that should be repeated from time to time to update the fingerprint databases.

A method to avoid laborious resurvey is based on use of everyday activity of plurality of persons inside a building while they are moving in a shopping mall or in an airport; each person has a mobile device capable to provide necessary measurements e.g. a smartphone equipped with a magnetometer, WiFi/BLE wireless module, etc. Collecting data by such method is very attractive because potentially it can help to avoid survey of the building.

The architecture of Coursa Venue that is illustrated by a Fig.1 allows to support both types of survey. Systematic survey is supposed to be used only once, to collect initial set of data and transfer them to cloud-based Coursa Venue cloud-based service where fingerprint databases are generated. Then fingerprint databases of the venue are transferred to users' portable devises.

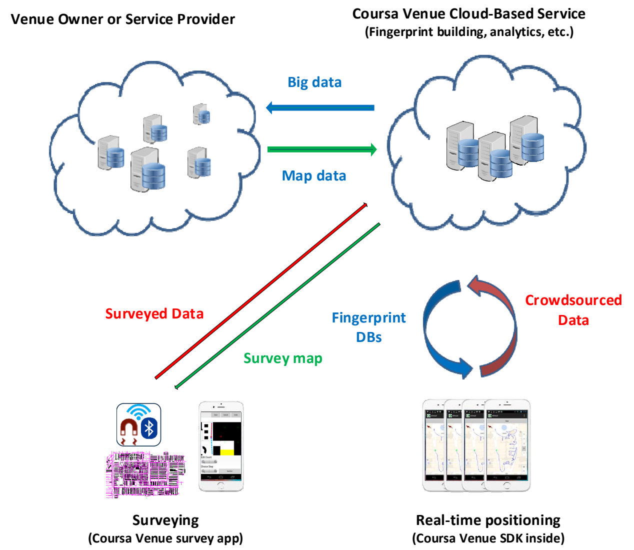


Fig. 1. Architecture of Coursa Venue platform

Android and iOS real-time mobile applications that run on the portable devices integrate Coursa Venue positioning SDK. The SDK realizes positioning based on fusion of inertial sensor data with radio and magnetic fingerprinting and provides mobile applications with user's coordinates in the world coordinate frame. The mobile application represents user position as a blue dot on the Google map.

Sensor data and other information collected during real-time navigation are transferred to the Coursa Venue cloud-based service where two-fold processing is realized. Firstly, these data are used for updating fingerprint databases that allows to avoid laborious periodic resurvey of the venue. Secondly, the data are intended to provide venue owners and services providers with market analytics, shopping history for advertising, mobile search, personnel activity tracking, and may serve for other purposes.

## III. Fusion of Several Positioning Techniques

In this section we discuss fusion of different positioning techniques used for indoor localization. A distinguishing feature of our approach is concurrent use of several positioning techniques to empower their advantages and diminish disadvantages. For example, magnetic fingerprinting usually delivers the most accurate positioning among other fingerprint techniques due to short-distance variability of magnetic field caused by metallic constructions of buildings. However, magnetic fingerprinting provides only local positioning because of ambiguity of magnetic field that usually leads to longer start of navigation. Though WiFi fingerprinting is often less accurate, it provides an unambiguous positioning that contributes to fast start of navigation and helps to recover from loss of tracking. Thus, combination of different FP techniques can increase accuracy and reliability of indoor navigation [9].

### *A. Particle Filter*

The indoor localization engine is built around the particle filter (PF) shown in Fig.2 that realizes heterogeneous data fusion. The ability of the PF to work in conditions of non-Gaussian noise and nonlinear measurement model gives to the proposed architecture a property to use measurements from the data sources of arbitrary nature.

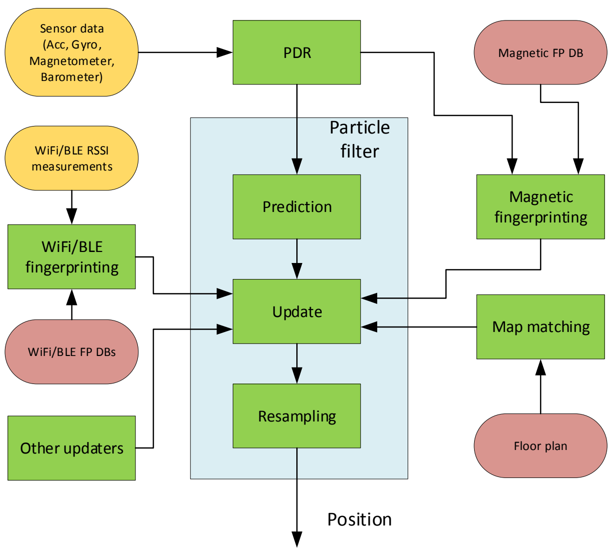


Fig. 2. Indoor licalization engine

Implementation of the PF contains three stages [11]: propagation, update or correction, and resampling that are continuously repeated. One more stage not shown on Fig. 2 is initialization of the cloud of particles, which is executed once. In the propagation stage, the coordinates and the heading of each particle are propagated using a pedestrian motion model. Data from the PDR module are used as the input of the propagation stage.

Let us consider each of M particles as a pair of Cartesian coordinates and a heading $(x_t^i, y_t^i, \theta_t^i)$, $i = 1, \dots, M$, $M$ is a number of particles, $t$ is a time index. Each particle is assigned with a weight $w_t^i$, depending upon probability density value to these coordinates.

In the prediction stage, the coordinates of each particle are propagated using the pedestrian motion model. Step length $l_t$ and heading change $\delta\theta_t$ from the PDR module are used as the input of the prediction stage. For example, the prediction stage can be written as follows:

$$\theta_t^i = \theta_{t-1}^i + \delta\theta_t^i \quad (1)$$

$$x_t^i = x_{t-1}^i + l_t^i \cos(\theta_t^i), \quad (2)$$

$$y_t^i = y_{t-1}^i + l_t^i \sin(\theta_t^i), \quad (3)$$

$$\text{where } l_t^i \propto N(l_t, \sigma_{lt}^2), \quad (4)$$

$$\delta\theta_t^i \propto N(\delta\theta_t, \sigma_{\delta\theta t}^2), \; i = 1, \dots, M, \quad (5)$$

$\sigma_{lt}$ and $\sigma_{\delta\theta t}$ are uncertainties of step length and heading change correspondingly,

$N(m, \sigma^2)$ is Gaussian probability density function with mean $m$ and dispersion $\sigma^2$.

Weights of particles are corrected in the update stage. The current measurements of RSSI from WiFi access points, measurements of the magnetic field and map constraints are used for this purpose. Such algorithms like WiFi fingerprinting, geomagnetic fingerprinting, and map matching transform the measurements into new particle weights by use of a likelihood function for the measurement model. The likelihood function is the probability of observing the measurement given the state of a particle. Due to independence of measurements for different positioning methods, the likelihood, as noted in [11], can be considered as a product of likelihoods of measurements for these methods (a similar approach was used in [10]).

Thus, new weight values are computed as follows:

$$w_t^i = w_{t-1}^i \prod_{j=1}^{K} p_j\left(z_t^j \middle| x_t^i, y_t^i, \theta_t^i\right), \; i = 1, \dots, M, \quad (6)$$

where $p\left(z_t^j \middle| x_t^i, y_t^i, \theta_t^i\right)$ is a likelihood function obtained based on measurements $z_t^j$ of $j$-th positioning method,

$K$ is a number of different positioning methods.

For example, in case of magnetic fingerprinting, measurement $z_t^j$ is 3D vector of magnetometer readings, whereas in case of WiFi/BLE fingerprinting it is RSSI from WiFi access points or BLE beacons.

After update, the weights of particles are normalized and, if necessary, resampled to prevent particles from exhaustion. As a result, user position is estimated at the PF output, e.g. by weighted averaging coordinates of all particles.

### *B. PDR*

The aim of PDR is prediction of user relative movement and estimation of a current smartphone orientation and misalignment. PDR is based on the pedestrian movement model so that a trajectory at a plane is divided into separate steps. The PDR input data are measurements from the 3D accelerometer, gyroscope and magnetic sensor. Raw measurements from sensors are filtered and synchronized. Filtered data are used in subsequent operations, which include step detection and attitude estimation. The attitude estimation includes orientation parameters as follows: change of an angle of user heading movement, smartphone orientation angles such as pitch and roll, and a device orientation matrix to transform from a device coordinate system to the horizontal plane, as well as the misalignment between the device heading and the direction of motion of the user.

For each detected step, PDR output data include position displacement and change of heading. These data are intended for use in the propagation stage of the PF. The device orientation matrix serves for transformation of a magnetic field vector into the horizontal plane in the magnetic fingerprinting module.

### *C. WiFi/BLE Fingerprinting*

The Wi-Fi/BLE fingerprinting module uses RSSI measurements to estimate user's position. The method essence is to compare a vector of RSSI measurements for an unknown position with data in the fingerprint DB that contains RSSI in known locations of the building. The WiFi/BLE-based position is used in the PF in the update stage to correct the weights of the particles. Due to its unambiguous feature, the

Wi-Fi fingerprinting helps to determine a starting position during initialization and to reduce time of start.

WiFi/BLE scan data and inertial sensors data are sourced from different hardware modules; they can be delayed from each other and have different sample rate. To provide effective fusion of these data, WiFi/BLE measurements are synchronized with inertial sensor measurements that allows to use them in the PF concurrently.

### D. *Magnetic Fingerprinting*

The magnetic fingerprinting module uses measurements of the magnetic field vector. The 3D magnetometer of a smartphone measures magnetic field in the device coordinate system. As the smartphone can be oriented arbitrarily in a user' hand or in a pocket among other use cases, the measurements are transformed to the horizontal coordinate system of an indoor floor plan. Device orientation angles required for the transformation are estimated by PDR. Geomagnetic fingerprinting is based on comparison of the measured magnetic field vector for an unknown position with data in a fingerprint map that contains magnetic field data in known locations. The result of comparing is used to update the weights of the particle in the PF.

### E. *Map Matching*

The purpose of the map matching algorithm is to refine a route of the user by matching the route with the building floor plan. Improvement of trajectory estimation is achieved by checking the permissibility of transition from one position to another one. The result of checking is used in the PF in the update stage. If transition of a particle is not allowed, its weight is set to zero. Thus, map constraints allow preventing from undesirable moving, e.g. from crossing walls or visiting restricted zones.

### F. *Other Techniques*

Besides mentioned magnetic fingerprinting, WiFi/BLE fingerprinting, and map matching, other techniques can be included in architecture of the indoor localization engine shown on Fig. 2, for example, BLE proximity beacons or position update from framework locations provided by the mobile operating system. Positioning techniques are not necessarily used concurrently. Some of them can be used during start of positioning process to set initial position whereas others can be used during continuous navigation. With the emergence of new data sources in smartphones, like for example WiFi RTT, the proposed architecture allows to use them in the hybrid solution to improve accuracy and availability of positioning.

## IV. Positioning Results

In this section we discuss positioning results with comparison to ground truth paths. Positioning results were obtained by use of real-time mobile applications with Coursa Venue SDK inside that provided indoor localization using PDR together with magnetic and WiFi fingerprinting. To provide real-time implementation of the PF on commercial smartphones, a number of particles was limited by an amount close to 1000.

We tested indoor positioning in different types of buildings, from retails stores to industrial venues to shopping malls for different users' behavior. Below, we show results of positioning in two types of buildings. The fist type is a retail store that features long and narrow aisles. Another type is a venue like a shopping mall or an office that differs from the first type by wider corridors.

### A. *Positioning in a retail store*

To estimate localization accuracy in a retail store, more than 100 tests were provided for different use cases and different routes of testers' walking. For every test, differences between user's current position and a reference position at the same instant were estimated. Integrated positioning errors that were assessed based on the differences for all trajectories are given in Table 1.

TABLE I.

| **Error** | **Use case** | | |
|---|---|---|---|
| | ***Smartphone in a pocket*** | ***Smartphone in a hand*** | ***All cases*** |
| Mean, m | 2.50 | 1.87 | 2.34 |
| Median, m | 1.96 | 1.77 | 1.91 |

Distribution of positioning errors among test trajectories is illustrated by a histogram shown in Fig. 3.

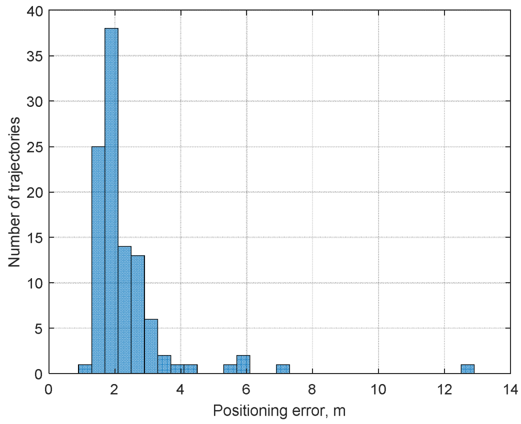


Fig. 3. Histogram of positioninig errors in a retail store

To illustrate details of positioning in retail store, we chose a typical trajectory from the test results for the store. Red line in Fig. 4 is the trajectory of a user who was walking in the retail store during 8 minutes with a smartphone in his pocket. Solid green line is a ground truth path.

Fig. 4. Example of positioning in a retail store. User's estimated positions are shown in red whereas ground truth path is given in green

Positioning error vs. time for this trajectory is shown in Fig. 5. An error up to 5 m in the initial part of the trajectory was caused by convergence process of particle filter just after start. After finishing the convergence process, root-mean-square error was 1.25 m.

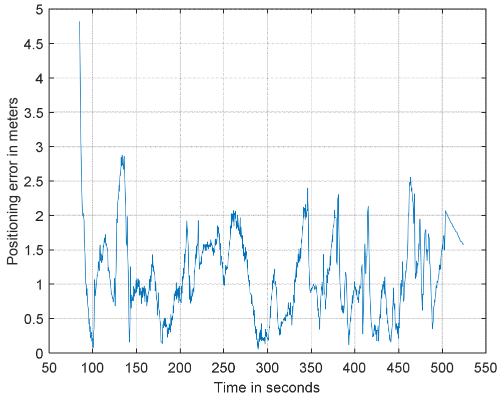


Fig. 5. Example of positioninig error vs. time in a retail store

### *B. Positioning in a venue*

To estimate localization accuracy in a venue, more than 200 tests were provided for different use cases and different routes of walking. PDR together with magnetic and WiFi fingerprinting were used for recovering user's positions indoors. For every test, positioning errors were estimated in the same way in previous subsection. Integrated positioning errors that were assessed based on the differences between user's current position and a reference position at the same instant for all trajectories are given in Table 2.

TABLE II.

| **Error** | **Use case** | | |
|---|---|---|---|
| | ***Smartphone in a pocket*** | ***Smartphone in a hand*** | ***All cases*** |
| Mean, m | 1.62 | 1.73 | 1.64 |
| Median, m | 1.34 | 1.73 | 1.37 |

Distribution of positioning errors among test trajectories is illustrated by a histogram shown in Fig. 6.

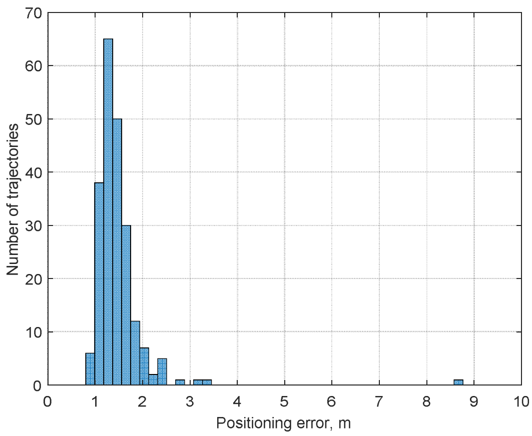


Fig. 6. Histogram of positioninig errors in a venue

Fig. 7 shows a typical trajectory from the test results for the venue. The trajectory of a user is shown in red. The user was walking in a shopping mall during 6 minutes with a smartphone in his pocket. Solid green line is a ground truth path.

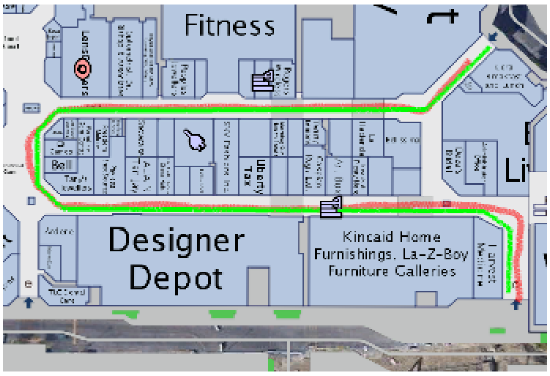


Fig. 7. Example of positioning in a shopping mall. User's estimated positions are shown in red whereas groud truth path is given in green

Positioning error is estimated as distance between user's current position and a reference position at the same instant. Positioning error vs. time for this trajectory is shown in Fig. 8. An error up to 6 m in the initial part of the trajectory was caused by convergence process of particle filter just after start. After finishing the convergence process, root-mean-square error was 2.08 m.

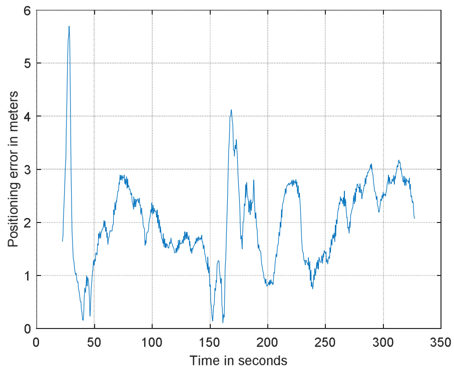


Fig. 8. Example of positioninig error vs. time in a shopping mall

### *C. Discussion of posiitoning results*

Positioning results shows that for both types of buildings – a retail store and a venue, we were able to reach indoor localization accuracy between 1 and 2 m in most tests. A narrow shape of histograms of positioning errors and closeness of mean and median errors demonstrate that only insignificant part of the trajectories have bigger errors. Localization errors for different use cases are very close to each other.

## V. Conclusion

We described the Coursa Venue platform that enables all phases of indoor positioning, from fingerprint maps creation to real-time navigation. Besides described capabilities, the navigation platform supports multi-floor positioning, automatic sensor calibration, seamless indoor-outdoor navigation, and other features that are helpful in practical use. We plan to discuss some of these features in future publications.

The test results confirmed achieving meter-lever accuracy of indoor localization due to fusion of inertial sensors with magnetic and radio fingerprinting without requiring new building infrastructure. Achieved level of indoor positioning accuracy gives an opportunity for venue owners to develop enhanced services that rely on positioning indoors.

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