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The IPIN 2019 Indoor Localisation Competition–Description and Results

FRANCESCO POTORTÌ[1], (Member, IEEE), SANGJOON PARK[2], ANTONINO CRIVELLO[1], (Member, IEEE), FILIPPO PALUMBO[1], (Member, IEEE), MICHELE GIROLAMI[1], PAOLO BARSOCCHI[1], SOYEON LEE[2], JOAQUÍN TORRES-SOSPEDRA[3,4], ANTONIO RAMÓN JIMÉNEZ RUIZ[5], ANTONI PÉREZ-NAVARRO[6], (Member, IEEE), GERMÁN MARTÍN MENDOZA-SILVA[3], FERNANDO SECO[5], MIGUEL ORTIZ[7], JOHAN PERUL[7], VALERIE RENAUDIN[7], (Member, IEEE), HYUNWOONG KANG[8], SOYOUNG PARK[8], (Member, IEEE), JAE HONG LEE[8], (Graduate Student Member, IEEE), CHAN GOOK PARK[8], (Member, IEEE), JISU HA[9], JAESEUNG HAN[9], CHANGJUN PARK[9], KEUNHYE KIM[9], YONGHYUN LEE[9], SEUNGHUN GYE[9], KEUMRYEOL LEE[9], EUNJEE KIM[9], JEONG-SIK CHOI[10], YANG-SEOK CHOI[11], (Member, IEEE), SHILPA TALWAR[10], (Member, IEEE), SEONG YUN CHO[12], (Member, IEEE), BOAZ BEN-MOSHE[13], ALEX SCHERBAKOV[14], LEONID ANTSFELD[15], EMILIO SANSANO-SANSANO[3], BORIS CHIDLOVSKII[15], (Member, IEEE), NIKOLAI KRONENWETT[16], SILVIA PROPHET[16], YAEL LANDAY[13], REVITAL MARBEL[13], LINGXIANG ZHENG[17], AO PENG[17], (Member, IEEE), ZHICHAO LIN[17], BANG WU[18], (Graduate Student Member, IEEE), CHENGQI MA[19], STEFAN POSLAD[18], (Member, IEEE), DAVID R. SELVIAH[19], (Member, IEEE), WEI WU[20], ZIXIANG MA[18], (Member, IEEE), WENCHAO ZHANG[21,22], DONGYAN WEI[21], HONG YUAN[21], JUN-BANG JIANG[23], SHAO-YUNG HUANG[23], JING-WEN LIU[23], KUAN-WU SU[23], (Member, IEEE), JENQ-SHIOU LEU[23], (Senior Member, IEEE), KAZUKI NISHIGUCHI[24], WALID BOUSSELHAM[25], HIDEAKI UCHIYAMA[26], (Member, IEEE), DIEGO THOMAS[27], ATSUSHI SHIMADA[27], (Member, IEEE), RIN-ICHIRO TANIGUCHI[27], VICENTE CORTÉS PUSCHEL[28], TOMÁS LUNGENSTRASS POULSEN[28], IMRAN ASHRAF[29], CHANSEOK LEE[29], MUHAMMAD USMAN ALI[30], YEONGJUN IM[29], GUNZUNG KIM[29], (Member, IEEE), JEONGSOOK EOM[29], SOOJUNG HUR[29], (Associate Member, IEEE), YONGWAN PARK[29], (Member, IEEE), MIROSLAV OPIELA[31], ADRIANO MOREIRA[32], (Member, IEEE), MARIA JOÃO NICOLAU[32], CRISTIANO PENDÃO[32], IVO SILVA[32], FILIPE MENESES[32], (Member, IEEE), ANTÓNIO COSTA[32], (Member, IEEE), JENS TROGH[33], (Member, IEEE), DAVID PLETS[33], (Member, IEEE), YING-REN CHIEN[34], (Senior Member, IEEE), TZU-YU CHANG[34], SHIH-HAU FANG[35,36], (Senior Member, IEEE), AND YU TSAO[37], (Senior Member, IEEE)

[1]Information Science and Technologies Institute, National Research Council (ISTI-CNR), 56124 Pisa, Italy
[2]Electronics and Telecommunications Research Institute, Daejeon 34129, South Korea
[3]Institute of New Imaging Technologies, Universitat Jaume I, 12071 Castellón, Spain
[4]UBIK Geospatial Solutions, 12006 Castellón, Spain
[5]Center for Automation and Robotics (CSIC-UPM), 28500 Arganda del Rey, Spain
[6]Faculty of Computer Sciences, Multimedia and Telecommunication, Internet Interdisciplinary Institute (IN3), Universitat Oberta de Catalunya, 08018 Barcelona, Spain
[7]AME-GEOLOC, University Gustave Eiffel, IFSTTAR, 44344 Bouguenais, France
[8]Department of Aerospace Engineering/ASRI, Seoul National University, Seoul 08826, South Korea
[9]HANA MICRON, Asan 336864, South Korea
[10]Intel Labs, Intel Corporation, Santa Clara, CA 95054, USA
[11]Intel Labs, Intel Corporation, Hillsboro, OR 97124, USA
[12]Department of Robotics Engineering, Kyungil University, Gyeongsan 38428, South Korea

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[13]Department of Computer Science, Ariel University, Ariel 50075, Israel
[14]Department of Electrical Engineering, Ariel University, Ariel 50075, Israel
[15]Naver Labs Europe, 38240 Meylan, France
[16]Institute of Control Systems (IRS), Karlsruhe Institute of Technology (KIT), 76131 Karlsruhe, Germany
[17]Department of Informatics and Communication Engineering, Xiamen University, Xiamen 361005, China
[18]Department of Electronic Engineering and Computer Science, Queen Mary University of London, London E1 4NS, U.K.
[19]Department of Electronic and Electrical Engineering, University College London (UCL), London WC1E 7JE, U.K.
[20]School of Geodesy and Geomatics, Wuhan University, Wuhan 430070, China
[21]Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
[22]University of Chinese Academy of Sciences, Beijing 100094, China
[23]Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, Taipei City 10607, Taiwan
[24]Department of Advanced Information Technology, Graduate School of Information Science and Electrical Engineering, Kyushu University, Fukuoka 819-0395, Japan
[25]ENSTA ParisTech, 91120 Palaiseau, France
[26]Library, Kyushu University, Fukuoka 819-0395, Japan
[27]Faculty of Information Science and Electrical Engineering, Kyushu University, Fukuoka 819-0395, Japan
[28]AraraDS, Santiago 8340457, Chile
[29]Department of Information and Communication Engineering, Yeungnam University, Gyeongsan 38541, South Korea
[30]Department of Computer Science, University of Gujrat, Gujrat City 50700, Pakistan
[31]Faculty of Science, Institute of Computer Science, P. J. Šafárik University (UPJS), 04001 Košice, Slovakia
[32]ALGORITMI Research Center, University of Minho, 4800-058 Guimar˜aes, Portugal
[33]imec-WAVES, Department of Information Technology, Ghent University, 9052 Ghent, Belgium
[34]Department of Electrical Engineering, National Ilan University, Yilan 26047, Taiwan
[35]Department of Electrical Engineering, Yuan Ze University, Zhongli 32003, Taiwan
[36]MOST Joint Research Center for AI Technology and All Vista Healthcare, Taipei City 10617, Taiwan
[37]Research Center for Information Technology Innovation, Academia Sinica, Taipei City 11529, Taiwan

Corresponding authors: Antonino Crivello (antonino.crivello@isti.cnr.it) and Joaquín Torres-Sospedra (jtorres@uji.es)

ABSTRACT IPIN 2019 Competition, sixth in a series of IPIN competitions, was held at the CNR Research Area of Pisa (IT), integrated into the program of the IPIN 2019 Conference. It included two on-site real-time Tracks and three off-site Tracks. The four Tracks presented in this paper were set in the same environment, made of two buildings close together for a total usable area of 1000 m^2 outdoors and and 6000 m^2 indoors over three floors, with a total path length exceeding 500 m. IPIN competitions, based on the EvAAL framework, have aimed at comparing the accuracy performance of personal positioning systems in fair and realistic conditions: past editions of the competition were carried in big conference settings, university campuses and a shopping mall. Positioning accuracy is computed while the person carrying the system under test walks at normal walking speed, uses lifts and goes up and down stairs or briefly stops at given points. Results presented here are a showcase of state-of-the-art systems tested side by side in real-world settings as part of the on-site real-time competition Tracks. Results for off-site Tracks allow a detailed and reproducible comparison of the most recent positioning and tracking algorithms in the same environment as the on-site Tracks.

INDEX TERMS Indoor localisation, indoor navigation, competition, benchmarking, smartphone-based positioning, foot-mounted pedestrian dead reckoning, Wi-Fi fingerprinting, magnetic field, camera-based positioning, inertial-based positioning, sensor fusion, Kalman filter, particle filter.

I. INTRODUCTION

Indoor positioning and navigation systems in the past decade have prompted considerable research activity both from academy and industry, due to the lack of readily available solutions able to provide indoor localisation information to location-based services. Despite the huge amount of technologies and techniques proposed and the many ones implemented, existing systems are not efficient or general enough to power off-the-shelf services as it happens with outdoor localisation. While systems for indoor localisation are commercially available, they are either too expensive or too tailored to a specific purpose or environment to be of general use, so their adoption is limited.

The main obstacle to widespread adoption of ubiquitous and seamless positioning and navigation applications is technological: not only indoor environments are diverse, but available technologies are complex and require expensive maintenance even for the most common environments. However, great progresses are being made from a technological point of view, so the next obstacles are starting to be in view, and these include privacy and standardisation issues.

In 2016 the first official standard was published on testing and evaluation of localisation systems: ISO/IEC-18305 [1] defines a common language and describes procedures and metrics for describing the performance of localisation systems from many points of view in a variety of indoor environments. This is a fundamental step towards widespread adoption, as the definition of common evaluation criteria is expected to add transparency to the market and eventually increase stakeholders' trust. ISO/IEC-18305 is but the first attempt at defining Test & Evaluation procedures, and its general applicability has been questioned [2]. Other efforts in the same direction have taken a hands-on approach, by involving system designers in annual competitions, such as the series of EvAAL, ISPN and IPIN competitions. But why is this necessary at all? In other words, why is it so difficult to compare indoor localisation systems?

Generally speaking, indoor localisation systems use a wide variety of sensors providing raw data. Data fusion techniques are used to refine the raw data, perform data analysis and generate position estimates. Such systems are intrinsically complex and have complex interactions with the environment, so their performance in the real world is subject to many different and possibly unexpected effects that cannot easily be reproduced in laboratory settings, where each technique is deeply analyzed, optimised and tuned. Another consequence of this complexity is that a simple comparison between two systems is not straightforward, as the evaluation involves many parameters depending on the specific use case. Offline comparison of localisation algorithms is possible through the use of open data sets [3], [4] that allow developers to work with the same data, gathered using the same technologies. As far as online comparison is concerned, the EvAAL evaluation framework [5] provides a set of procedures useful for on-site test and evaluation.

The EvAAL framework has been used for the EvAAL competition series (2011–2013) and has been promoted by the International Conference on Indoor Positioning and Indoor Navigation (IPIN) as the basis of the IPIN Competition series (2014–2019). The IPIN conference is open to experts and stakeholders in the indoor localisation field; every year it involves around 300 attendees. This paper describes the 2019 edition of the IPIN Competition held in Pisa, Italy, from 28 to 29 September 2019. Besides describing organisational aspects and technical choices taken by the organisers, the core part of the paper is represented by a description of the systems proposed by competitors in four different Tracks: on-site smartphone, on-site video, off-site smartphone and off-site foot-mounted IMU (Inertial Measurement Unit). Details about each Track are given in section III.

This work provides the reader with a unique overview on the directions taken by the research community, what are the practically used technologies and what is the performance that can be expected by real systems in a real-world scenario. It describes state-of-the-art systems tested side by side in a realistic environment on a level playing field. The two on-site Tracks put system designers and developers in a challenging situation with little time to tune their systems to the environment. The two off-site Tracks gave designers the opportunity to test in detail their algorithms in a completely reproducible synthetic environment. All were compared according to the EvAAL framework, in the same physical setting.

The paper is structured as follows. Section II gives an overview on other indoor positioning and localisation competitions. Section III describes the competition setting, measurement procedure and overall results. Sections IV–VII are devoted to the four Tracks with an overview and detailed description of competing systems. Sections on Lessons Learned and Conclusions close the paper.

II. COMPETITIONS ABOUT POSITIONING, LOCALISATION AND NAVIGATION

The first international indoor localisation competition series was EvAAL, in three editions from 2011 to 2013 [6]. EvAAL was set in a living lab, a small real house instrumented with all sort of sensors. An actor was wearing the competition system and walked for a total of about 50 m on a precisely-defined path where individual footsteps were marked on the floor and a chime ensured that the actor performed one step per second. Competitors had one hour to instrument the room with their equipment before the evaluation took place. Scoring was based on point accuracy (third quartile of the error estimated twice per second) and other hard and soft metrics such as installation time, system reliability, adherence to open standards and user acceptance.

In 2014, the international conference on Information Processing in Sensor Networks (IPSN) hosted the first of five editions of the Microsoft indoor localisation competition [7]. The competition offered a measurement environment similar to a laboratory setting, thus allowing for a wide participation of prototypal systems. In particular, competitors had to position their system on a series of markers, and they were asked to estimate the coordinates of these markers. The indoor environment was not set to reproduce a specific use case, and from 2014 until 2018 the settings varied between few rooms and 600 m^2. Scoring was based on the mean accuracy. Recently, the competition considered also a 3D Track. The main competition strength was inclusiveness: the setting was similar to a lab, so many teams were able to participate, usually exceeding 20 participants. The main weakness was that the environment was not representative of a real use case, being based on a sequence of static localisation accuracy measurements.

The first of six editions of the IPIN Competition series was held at the IPIN 2014 Conference, located in Busan, South Korea. This competition strived to keep as much as possible of the EvAAL rigour and realism, while extending it to a wider environment. The result was the definition of the EvAAL framework [5], on which all subsequent IPIN Competitions would be based [8]. Competitors were not allowed to install their own equipment in the environment, which was a large public area. Similarly to the Microsoft competition, the organisers set a number of key points along a path and the scoring relied only on point accuracy. The competitors' systems worked in real-time, but measurements were done on an actor wearing the competing system who walked at a natural pace on a path about 600 m long including stairs, during which the competing system was expected to log two position estimates per second. All in all, this was a very challenging test for systems that were often at the prototypal stage and whose designers only had the previous day to survey the competition area, without advance knowledge of the competition path. In addition, systems were expected to run on a commercial smartphone, without any external sensors. Since no instrumentation on the competition area was allowed, only the already deployed Wi-Fi access points and the map knowledge could be exploited by competitors in addition to the built-in smartphone sensors.

More in detail, in 2014 the area was a multi-floor building used for conferences and big events, and the path spanned three floors connected by staircases. Reference points were marked on the floor with adhesive sheets and were used as ground truth. Competitors gave their phone to an actor who had to follow a predefined path with the only constraint of naturally walking and passing over all key points in the right order. In the IPIN 2015 edition, held in Banff (CA), the competition consisted of two on-site Tracks (smartphone-only and foot-mounted IMU) and one off-site Track (Wi-Fi fingerprinting in large environments). The idea of the off-site Track was about improving the development of algorithmic techniques: competitors were provided with some signal traces gathered into three building at a university campus and they were asked to estimate the path which had generated those traces. Similar mixes of on-site and off-site Tracks were proposed during the IPIN Competition editions 2016, 2017, and 2018 [9]. In 2018 and 2019, on-site and off-site tracks have taken place in the same indoor environment.

In 2018 the PerfLoc project launched a one-time competition, gathering smartphone system competitors in a challenging environment [10]. The main goal of PerfLoc is to facilitate the development of the best possible smartphone indoor localisation apps. In a way analogous to the UIJIndoorLoc data set, PerfLoc publishes an extensive repository of annotated smartphone sensor and RF signal strength data to enable researchers to test smartphone indoor localisation algorithms [3], [4]. Moreover, they provide a web interface for competitors to obtain a score for their estimates immediately. Measurements conform to ISO/IEC 18305 [1], [2].

In 2019 the IEEE Communication Theory Workshop[1] organised the Positioning Algorithm Competition, an offline challenge whose purpose was to design and train a positioning algorithm based on estimated channel frequency responses between the user and an antenna array. Competitors had to develop an algorithm using a data set created with a channel sounder. All algorithms would be tested on the day of the competition on unseen test data comprising only channel responses, without the ground truth.

The sheer existence of these initiatives demonstrates the presence of widespread interest in evaluation of indoor localisation systems among researchers, both in academy and industry. The following sections describe the IPIN 2019 Competition, with both on-site (real-time) and off-site (offline) Tracks.

III. EVALUATING INDOOR POSITIONING SYSTEMS IN A RESEARCH CAMPUS

The IPIN 2019 Competition was held in a research campus, namely the Pisa research Area of the CNR (Italy's National Research Council). It consisted of four Tracks, each managed by Track chairs under the supervision of the competition chairs Francesco Potortì and Sangjoon Park.

Institutions involved were the Institute of Information Science and Technologies (ISTI) of the National Research Council (CNR, IT), the Institute of New Imaging Technologies (INIT) from the University of Jaume I (ES), the GEOLOC laboratory of the French Institute of Science and Technology for Transport Development and Networks (IFFSTAR, FR), and the Electronics and Telecommunications Research Institute (ETRI, KR).

A. PREPARING THE COMPETITION TRACKS

Under the umbrella of the EvAAL framework, five Tracks provided an exciting variety of situations, all of them centered on personal localisation. The first four Tracks were all set in the same area, two on-site and two off-site ones, which makes for potentially interesting comparisons, especially as some teams participated in more than one Track, some of them using the same methods in on-site and off-site Tracks.

On-site Tracks are the most challenging, as they require competitors to prepare a working system at their premises, integrate it with the measuring app used both for gathering the estimates and marking the passage on the key point markers, spend a single day in the competition area for surveying the (large) area, take measurements and test the reliability of their system, and finally undergo two trials, of which the best score is taken. The trial itself lasts for about fifteen minutes during which an actor walks while carrying the competing system; the system under measure must not crash, and no further tuning is possible. No wonder that few competitors participate each year to such an exciting yet difficult competition, and no surprise that, with few notable exceptions, those who manage to get a meaningful result are not beginners, but teams with significant research and hands-on experience. Here, when we speak about a "meaningful result" we mean something that could be useful in practice, that is with the system running from start to end of at least one trial and obtaining a score (third quartile of error) under 15 m.

Off-site Tracks are less challenging, and in fact they see higher participation and better scores, mainly because competitors can carefully tune their systems to the specific environments without any strict time constraint. An interesting point of off-site Tracks is that competitors share the same data, which can be used in the future for testing new algorithms and rigorously comparing them with today's state of the art, something which is not possible for the on-site Tracks.

Starting from the above considerations, the competition chair made several decisions, which were then discussed and approved by the Track chairs. The first decision was that using the same location for all Tracks is a plus and should be an aim of the competition, meaning that chairs of Tracks 3 and 4 had to travel to the competition site some months in advance for a survey and measurements. At the same time, it was important to avoid using the same markers for different Tracks, and even to avoid using similar paths overall, lest competitors applying for more than one Track

[1] https://ctw2019.ieee-ctw.org/authors/

were advantaged by this knowledge. This was particularly important for competitors participation in off-site Track 3, who had received maps and measurements well in advance and should not have been able to exploit this knowledge when preparing for competing in on-site Tracks 1 and 2. As part of this effort, Wi-Fi measurements were anonymized to prevent competitors from reusing for on-site Tracks a radio map that had been generated with the off-site measurements.

The second decision was setting the path for on-site Tracks to be no longer than 15′ and 600 m, which is long enough to be challenging for competitors, but not longer. In fact, one should considered that actors walked that path to survey and learn it, run the trials and repeat after an error: all in all 10–20 times each, which takes time and energy. A tired actor risks making errors and having to restart the path from scratch; moreover, we had a single day to complete the competition, and any unanticipated severe inconvenience risked having the organisers exceed the time available to complete all the trials. This was to avoid at all cost, as all competitors had put a great deal of effort in preparing and participating in this competition, and their satisfaction was considered of the utmost importance.

The third decision was to try and fit the EvAAL framework as strictly as possible. As detailed in [5], the EvAAL framework includes four *core* criteria which are the distinguishing features of the EvAAL framework:

1) Natural movement of an actor
2) Realistic environment
3) Realistic measurement resolution
4) Third quartile of point Euclidean error

All Tracks fit these criteria. Additionally, the *extended* criteria are:

1) Secret path
2) Independent actor
3) Independent logging system
4) Identical path and timing

It is easy for off-site Tracks to respect these criteria, while on-site Tracks can only approximate them.

A further decision was striving to keep the path secret by applying the marks on the floor just before the start of the competition, and asking the competitors to stay inside the competitor's room for the whole duration of the competition, which was not easy because the competition lasted several hours and often some time elapsed between the first and second trial of each competitor. However, this was an improvement over previous editions, when competitors were free to wander around the building even after the start of the competition.

An independent actor (one member of the organiser's team) walked the path for both Tracks 1 and 2, while in previous editions this was done only for Track 1, mostly because Track 2 requires carrying special equipment, so instructing the actor on how to use it was not always easy.

An independent logging system was used for Track 1, as in past editions, and also for those teams of Track 2 whose system run on a smartphone.

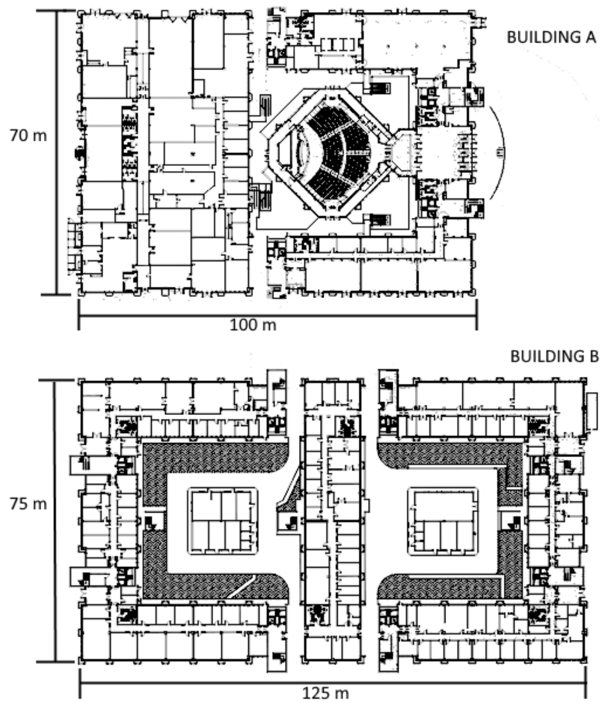

FIGURE 1. **Ground floor map of the usable indoor area**

As in previous editions, the path was too long to force identical path and timing for all trials. In practice, the times needed by the actor to walk the entire path was in the range from 11′6″ to 15′2″, depending on their walking speed.

B. MAPPING THE CNR AREA

The location used for the IPIN 2019 Competition is a ''CNR Area'' hosting a dozen research institutes belonging to CNR (Italy's National Research Council), for a total of over 2500 among staff, PhD students and research associates. The area is composed of several buildings. The evaluation path and the allowed area for the competitors' survey included significant parts of the largest two buildings, both three floors above ground, and the outdoors area around them.

The usable indoor area depicted in figure 1 spans about 6000 m^2 on three floors, to which a surrounding outdoor area of about 1000 m^2 should be added. The usable indoor area is mainly composed of corridors but also includes an auditorium and a canteen, with lifts and staircases connecting floors. Corridors are straight and meet at 90°, they are about 2.5 m wide and 2.7 m high. They are visually very similar to each other, and in fact it is easy to get lost in the building even for people used to it. Wi-Fi access points cover the whole area, indoors and outdoors.

As an example of the general criteria used to create the evaluation paths for all Tracks, Track 1 chairs imagined a typical walk done by staff during a normal working day. The actor starts from the first floor in building B (see figure 1), reaches the auditorium at the ground floor of building A and then the canteen. During this first section of the path the actor goes through three fire doors and a staircase. In the canteen, the actor sits down for 60 s to simulate a lunch break, then reaches a meeting on the second floor of building B. This second part of the path includes a 50 m outdoor walk connecting two buildings, plus two staircases, two lifts, and four fire doors. The path goes through 75 key points for a total length of 544 m, which the actor walks in about 15 minutes.

For all Tracks, positioning the key points is done so that they are no closer each other than about 2 m and not farther away than about 10 m indoors, with an average distance of about 7 m. key point positions were carefully measured using a laser distance meter with respect to the walls and then accurately reported on a georeferenced map using Qgis.

For on-site Tracks 1 and 2, key points are placed in such a way that, when the actor walks over a key point, the next one is always in sight. This (loose) constraint was put in place to ease the actor's job, because if a key point is missed or walked over in the wrong order, the actor needs to restart the path from the beginning.

Georeferencing was done by getting the coordinates of many reference points of the Google maps satellite view and feeding them to Qgis. The inaccuracies deriving from this procedure are irrelevant as far as the indoor path is concerned, as the georeferenced map was shared with the competitors. Hence, the indoor reference system was the same for all. Inaccuracies could arise on the external path, but we can argue that the problem is minor for several reasons. First, the outdoor path included few key points; given that the measure is based on the third quartile, a couple of errors larger than normal have little influence on the result. Second, we measured the GNSS readings of these points on some smartphones and the error was in the range of 1 m with respect to our georeferenced map. Third, the outdoor path was quite short and simple, and the whole area was covered by many Wi-Fi signals, so competitors could keep using the same pdestrian dead reckoning (PDR) and radio sensing algorithms as indoors. Fourth, the position of doors was known to competitors beforehand, thus preventing the possibility of significant errors while entering and exiting the buildings.

C. MEASURING THE PERFORMANCE OF COMPETING SYSTEMS

Competitors of the on-site Tracks were provided with *StepLogger*, a measurement app for Android with two functionalities. The first is interfacing with the competing app by receiving and logging periodic positioning estimates. The second is displaying a button with a label on it that the actor taps when walking over the same-labelled key point.

StepLogger logs the positions, estimated by the competing app with a suggested rate of twice per second. The estimated position is logged to a file. A log entry reads as `[time, x, y, z]` where *time* is in milliseconds from the Unix epoch, x and y are longitude and latitude expressed in decimal form with at least six decimal digits and z is the floor as an integer.

The reason why we use an app to log the estimates rather than letting the competing app do it is to discourage cheating on timestamps or recomputing of past coordinates, given that we want to measure the real-time performance of competing systems.

StepLogger displays a big button with the same label as marked on the next key point along the path. When the actor approaches the key points, he checks that the label on the marker is the same as the button's and prepares to tap the button the moment he is precisely over the marker. Upon tapping the button, StepLogger logs the label and a timestamp to a second file, and displays the next label on the button. Each log entry reads as `[time, label]`. The reason why the label is shown on screen is for the actor to check that he is following the right path and has correctly tapped once per key point.

The two log files are saved on the smartphone and given to the organisers at the end of each trial. Together with a third file, which is unknown to the competitors and contains the ground-truth positions of the key points, they provide all the information needed to evaluate the point errors and compute their third quartile, which is the final result. The Octave application Evaalscore is used to produce all the statistics, graphical output and a movie representing the path and estimation errors, useful for organisers and competitors. The source code of Evaalscore and its output computed over the competitors' results is available at `http://evaal.aaloa.org/2019/detailed-results`.

StepLogger runs in the foreground, while the competing app which estimates the device position acts as a background service. The integration between the two apps exploits the AIDL formalism (Android Interface Definition Language). The AIDL file defines the interface `IStepLoggerService` which implements the `logPosition(timestamp, x, y, z)` method. The competing app can discover and bind to a provider of `IStepLoggerService` by following two simple steps:

- create an Android Intent with `BOUNDSERVICEPACKAGE` set to an `BOUNDSERVICECLASS` set to StepLoggerService;
- invoke the `bindService(...)` method in order to bind to the Android service implementing the `IStepLoggerService` interface.

The StepLoggerClient app is a development aid mimicking the expected behaviour of a competing app. Last, StepLoggerV2 is a modified version of StepLogger which runs in the background, thus allowing the competing app to run in the foreground. Figure 2 shows a screenshot of StepLogger, StepLoggerClient and StepLoggerV2, respectively. The software package is available at http://evaal.aaloa.org.

D. COMPETITION RESULTS

The "accuracy score" for each trial was computed for each team by comparing the estimated coordinates with the ground truth, that is reference coordinates of the key points marked on the ground along the path. This metric combines the floor detection accuracy and the horizontal positioning error.

$$\varepsilon = \|\mathbf{P_R} - \mathbf{P_E}\| + p \cdot |f_R - f_E| \tag{1}$$

TABLE 1. Results for all Tracks. The first column is the competition score (equation 2.

Track	Team	Score 3rd quartile [m]	Mean [m]	RMSE [m]	Median [m]	95th percentile [m]	Floor detect rate [%]	Section reference
Track 1	SNU-NESL	3.8	3.3	4.4	2.6	7.3	100.0	IV-B1
	TLBS	7.4	7.1	12.4	3.6	28.8	91.8	
	STEPS	12.9	11.7	14.9	9.8	19.8	100.0	IV-B2
	MITLab	24.2	22.7	34.1	16.9	85.5	76.7	IV-B3
	YNU-MCL	65.5	37.8	52.0	26.2	112.4	100.0	IV-B4
	INDORA	75.3	57.5	62.9	59.9	100.9	41.1	IV-B5
Track 2	HANA Micron	3.6	4.3	6.8	2.2	18.6	100.0	V-B1
	Ariel	8.5	5.7	9.0	2.1	25.3	91.8	V-B2
	XMU	14.8	7.8	12.5	1.7	28.5	100.0	V-B3
	Kyushu Univ.*	108.8	82.8	92.5	88.1	156.0	63.4	V-B4
Track 3	INTEL LABS	2.3	2.0	2.6	1.5	6.2	100.0	VI-B1
	Naver Labs EU	2.4	1.7	2.1	1.3	4.4	100.0	VI-B2
	IOT2US	2.5	2.1	2.6	1.8	5.5	100.0	VI-B3
	AraraDS	2.6	1.9	2.4	1.5	4.9	100.0	VI-B4
	TENCENT	2.7	1.9	2.4	1.4	4.8	100.0	
	XIHE	2.9	2.4	3.2	1.7	6.9	100.0	
	UMinho	3.0	2.4	3.0	2.0	6.0	100.0	VI-B5
	FINEWAY	3.5	2.7	3.6	1.9	8.4	100.0	
	UGent	4.1	3.4	4.4	2.4	8.9	100.0	VI-B6
	TONJGI	5.1	4.2	5.5	3.2	12.0	98.9	
	INDORA	6.6	3.9	5.8	2.0	12.6	100.0	VI-B7
	YAI	6.9	5.0	6.4	4.3	12.3	100.0	VI-B8
Track 4	KIU SNU	1.6	1.2	1.5	1.0	3.2	100.0	VII-B1
	KIT	1.7	1.4	1.8	1.1	3.8	100.0	VII-B2
	AOE	3.5	3.1	3.3	3.0	4.8	100.0	VII-B3

* The provided estimations did not include all evaluation waypoints

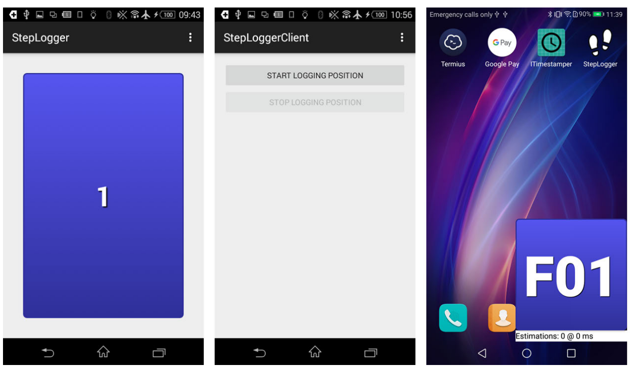

FIGURE 2. Screenshots of the released app.

where

- $\mathbf{P_R}$ is the vector with the ground truth horizontal coordinates
- $\mathbf{P_E}$ is the vector with the horizontal coordinates estimated by the competitors
- $\|\mathbf{P_R} - \mathbf{P_E}\|$ is the horizontal error, and it is computed as the Euclidean distance between the ground truth and the estimated position provided by the competitor in the 2D space.
- p is the base floor estimation error penalty and is set to 15 m.
- $|f_R - f_E|$ is the absolute difference between the actual floor number and the estimated one.

The point error ε is computed for all key points marked on the ground that define the path of a specific challenge.

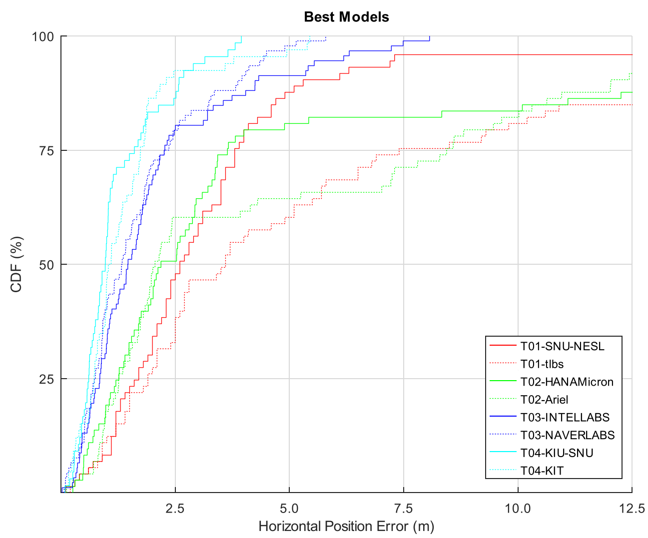

FIGURE 3. Cumulative distributions of point errors (equation 1).

The "accuracy score" s is given by the third quartile of ε:

$$s = 3^{\text{rd}}\text{quartile}\,\{\varepsilon\} \tag{2}$$

The team with the lowest score wins the challenge. Table 1 shows the scores for all the four Tracks. Some additional metrics included in the ISO 18305 Standard are also reported in the table. Figure 3 depicts the cumulative distributions of the accuracy score s for the winners and runners-up of the four Tracks.

IV. TRACK 1 - SMARTPHONE-BASED (ON-SITE)

A. TRACK DESCRIPTION

The purpose of the first on-site Track, namely ''smartphone-based'', is to assess and measure the ability of competing systems to accurately identify their position inside a large, public indoor area using a hand-held smartphone only. To this purpose, competitors are requested to develop a smartphone application able to estimate indoor positions in real-time. Only one commercially available smartphone per competitor can be used. The competing app must run entirely on the smartphone and can use any built-in sensor available (i.e. no access to remote services like external databases or remote servers is allowed). The app is integrated with the measurement app (see section III-C.

Competitors are provided in advance with a detailed map of the area, while the chosen path for the competition is disclosed only when the competitors start the trial. Teams can access the area the day before the competition to survey the area themselves, take measurements where needed (e.g. make measurements of the Wi-Fi network signals) and ensure that their app interacts correctly with the measurement app.

On the day of the competition, for each team, an independent actor walks along the reference path while holding the smartphone in hand. At the beginning of the trial, the competing team can very briefly configure their smartphone. Next, the actor starts to walk at a natural pace along a loosely-defined reference path, equal for all competitors. The path connects some tens of key points identified by markers placed on the floor, spanning multiple floors and multiple buildings. The list of IDs and positions of the key points is the ground truth. When the actor steps above each key point, he sets a time mark using the measurement app. The actor is not required to keep the phone in any specific position or orientation: typically the actor moves his hand freely and taps on the screen at key points. We estimate that a trained actor will generate timestamps with an error smaller than 250 ms in time and less than 0.5 m in space. When the actor makes an error, like forgetting to tap on the screen or missing a key point, the trial is stopped and restarted.

The competing app provides estimated coordinates with a suggested frequency of 2 Hz to the measurement app; only the last estimate before each time mark is taken into account when evaluating the competing system accuracy. The competing app must provide (x, y, z) coordinates in the WGS84 coordinate system, where x is longitude, y is latitude and z is the floor number, 0 being the ground floor. For all competitors, the actor needs approximately the same time to follow the path, passing through all the key points in the same order. The path includes pauses, loops and any kind of natural movement. Each team of competitors has two trials, and the best score is used as the final result.

The path shown in figure 4 spans areas with different characteristics chosen to be challenging for competitors: straight corridors alternate with small and medium open areas such as the auditorium and the canteen. If, on one hand, staircases are well managed by systems based on pedometers, on the other hand the presence of lifts requires a careful evaluation of signals such as Wi-Fi and barometer. Systems based on magnetic field could suffer in some regions, for example when the actor nears a closed fire door or stops in front of a business coffee machine.

B. INDOOR POSITIONING SOLUTIONS PROVIDED BY COMPETITORS

1) SNU NESL TEAM

SNU NESL is based on PDR, which can be performed solely using inertial sensors without need of any infrastructure. When a PDR system is mounted on the foot of a pedestrian, zero velocity update (ZUPT) can be performed during the stance phase, where the IMU remains still for a short time in the middle of a step [11]. ZUPT compensates for the drifting errors generated by integrating low-cost MEMS inertial sensors when using the conventional strapdown INS algorithm, or integration approach (IA).

If a PDR system is implemented on a handheld device, ZUPT cannot be applied, making the integrated navigation solution diverge in a short time. In this case, the parametric approach (PA) can be applied [12]. PA-based PDR does not provide continuous information. Instead, the current position is computed at every step using the estimated heading and distance between two subsequent steps.

a: PA-BASED PDR

The output of a PA-based PDR system is as many 2.5D position vectors as the number of steps the user made. The block diagram is shown in figure 5. The magnetometer in addition to IMU is used to perform three main procedures.

Once a step is detected, user position can be updated using the heading and step length as in (3).

$$\begin{bmatrix} p_{n,k} \\ p_{e,k} \end{bmatrix} = \begin{bmatrix} p_{n,k-1} \\ p_{e,k-1} \end{bmatrix} + l \begin{bmatrix} cos(\psi) \\ SIn(\psi) \end{bmatrix}. \tag{3}$$

where p is the position of the user with subscript k for the k^{th} step, and subscripts n and e for the north and east direction, respectively. l and ψ denote the estimated step length and heading, respectively.

The name PA mainly originates from step length estimation model. The distance between the two steps is determined from the fixed parameters. As some earlier work suggests, there is a linear relationship between step length and walking frequency [13]. There are numerous other features such as the accelerometer variance which can be used to estimate the step length depending on the mounting position of the IMU. But assuming that step is correctly detected, using only the walking frequency makes it possible to mount the IMU on an arbitrary position. Equation (4) shows the parameterised step length, where WF stands for walking frequency.

$$l = \alpha \cdot \mathrm{WF} + \beta. \tag{4}$$

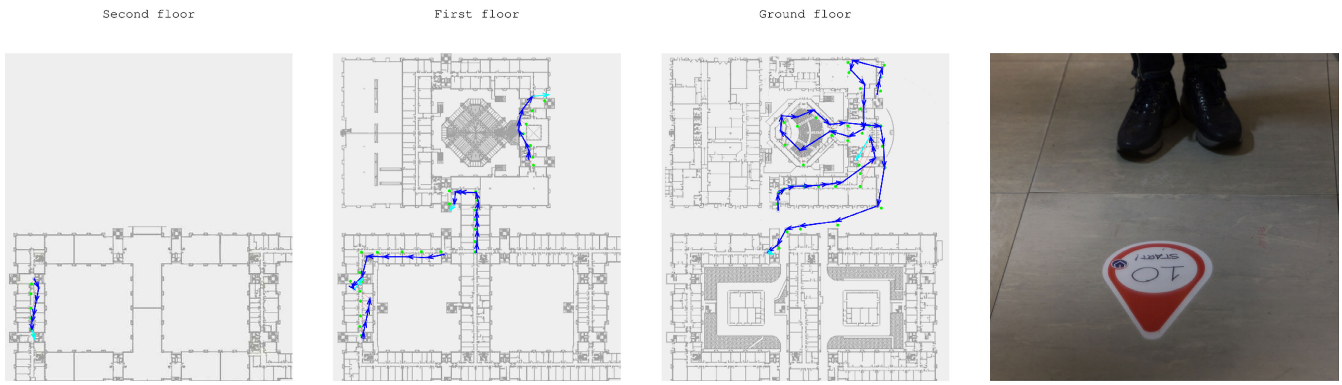

FIGURE 4. Track 1 and Track 2 multilevel path and example of key point.

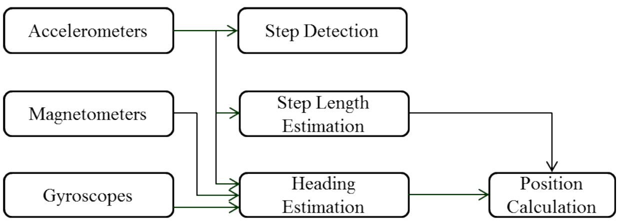

FIGURE 5. Block diagram of PA-based PDR.

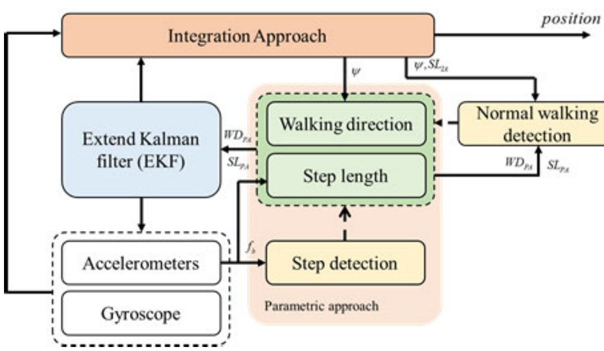

FIGURE 6. Block diagram of IA-PA fusion.

b: COMPENSATING THE ERRORS OF PA

Two of the main error sources of PA-based PDR system are the heading offset and the step length accuracy. First, the heading of the device and the user are assumed to be the same, and if the assumption does not hold, it can result in large errors. Even if the step length parameters regressed from huge amount of data are used, uncertainty surely exists among the parameters. We fused IA- and PA-based PDR systems to compensate for the two errors as shown in figure 6.

Three different conditions are possible depending on the walking scenario. First, when the user is walking in a straight, normal condition and the heading offset is small, both the step length and walking direction from the PA module are assumed valid.

If the user is walking in a normal condition but the device heading does not match the user's, the estimated step length from PA can be used as a measurement for the IA module. Finally, if the step length computed from IA is a lot shorter than the estimated value from PA, pure INS is performed without using the output of the PA module. Such cases may correspond to a turning of the user or a transition between different mounting positions.

2) STEPS TEAM

STEPS is a smartphone indoor positioning system based on recent AR (Augmented Reality) and Mixed Reality tools such as Google's ARCore or Apple's ARKit. The AR tools are used as a visual pedometry (scaled optical flow) sensor, which is then fused with an advanced version of localisation particle filter to produce a both accurate and robust solution for various indoor positioning applications. The presented method allows a simple and efficient mapping solution that, combined with the localisation particle filter, allows 1–2 m positioning accuracy in many standard indoor scenarios. While a naive algorithm is relatively time efficient, its precision might be insufficient in cases of large areas with few constraints. In this section we proposes a particle filter-based algorithm with advanced methods to improve accuracy and robustness.

a: FLOOR-CHANGE DETECTION

In order to generalise the localisation algorithm from 2D to 3D (i.e., 2.5D) we need to define a method for detecting floor change. An error of "wrong floor" is both significant for the user and may cause significant errors related to wrong constrains applied by the "wrong map". At first we used both barometer sensor and 3D optical flow in order to estimate the elevation of the user. Both methods are relatively sensitive to changes in the elevation, yet both tend to drift. Moreover, 3D optical-flow methods will not be able to detect vertical movement in an lift. Therefore, we have designed the following *floor-change* filter which is mainly based on rapid changes in the barometer readings[2] (for simplicity we assume that the barometer sampling rate is fixed):

[2] An improved algorithm may also fuse the 3D optical-flow sensor reading with the barometer sensor using a Kalman filter.

1) On start, let z_0 be the initial altitude – estimated according to the barometer output, let $\Delta z_0 = 0$, let $p < 1$ be some positive parameter, usually related to the barometer sampling rate, e.g., $p = \frac{1}{Hz}$.
2) On barometer reading (z_i), let $\Delta z_i = p(z_i - z_{i-1}) + (1-p)\Delta z_{i-1}$
3) If $\Delta z_i > C_{up}$ (some positive elevation rate) assume the user is going up;
4) else if $\Delta z_i < C_{down}$ (some negative elevation rate) assume the user is going down;
5) else assume the user is on a flat floor, if the user was going up or down estimate the elevation-change between the current z and the last flat-floor parameter.

Initially when no knowledge about the current floor if provided, the particles are randomly spread among all floors.

b: MAPPING

The advanced particle filter algorithm relies on the existence of a pre-made map of the region of interest. Such map is assembled by our system using the following technique:

1) AR measurements tools surface detection, which allows us to conclude the sampled region of interest boundaries;
2) map representation in the form of painted image, using the defined colors: A, B, C, D to represent the verity of the different constrains.

The colors will be placed on the map according to the following logic:

- **A**: accessible area;
- **B**: inaccessible area, such as walls, fixed barriers, etc. as sensed by AR tool;
- **C**: partially accessible regions: this area represents locations with relatively low probability for a user to stay (e.g., tables);
- **D**: floor changing regions, such as stairs, escalators and lifts.

A 2.5D map such as presented in figure 7 will be the base for the particle filter algorithm, and will later on be used to determine the particles grade.

c: VELOCITY ESTIMATION

Indoor navigation methods often use the device IMU sensor in order to implement a pedometer which detects the device global orientation and counts "steps". Yet, such method introduces significant inaccuracy both in the measured distance and in the orientation i.e., some steps are larger than other and the device orientation is only loosely correlated with the walking orientation. Therefore, we use optical flow with plan and range detection [14] in order to estimate the user movement with high sampling rate, which allows an improved distance approximation and fusing optical features to reduce IMU drifts.

d: PARTICLE FILTER FOR LOCALISATION

This section discusses possible naive particle filter algorithm for localisation estimation.

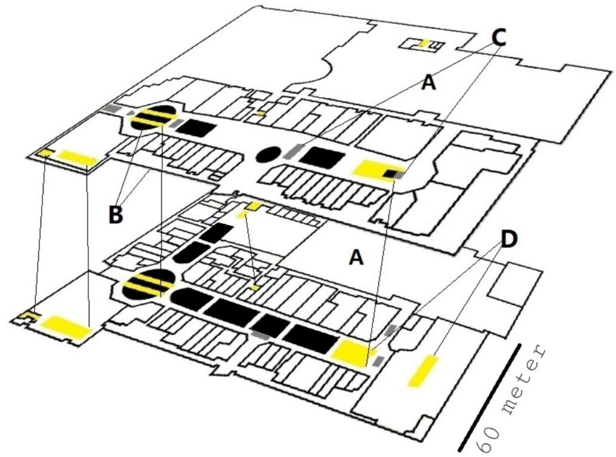

FIGURE 7. **2D multicolor map example used in the advanced algorithm. White (A) represents accessible areas, black color (B) represents fixed ares (in this case walls), grey (C) represents dynamic inaccessible areas (tables in this case) and yellow (D) represents stairs and lifts.**

A particle filter represents the posterior distribution of a set of particles P ($|P| = n$) on a given map; the result of such algorithm (for each step) is a new set of particles P' with a (slightly) different distribution. The goal of this algorithm is to get all the particles to converge in one area on the map in a few steps (re-sampling). After converging, the internal state (location) will be the average location of the best particles (the ones with the highest grades).

Algorithm 1 explains the process of the particle filter method using mobile pedometry sense.

e: SOFTWARE INTERFACES

The proposed system is based on the following interfaces:

Algorithm 1 Generic Particle Filter Localisation Algorithm: A Black and White Map Is Used in Order to Present the Geo-Constrains Used by the Particle Filter

Input: Black and white 3D map of the navigation area.
Init: generate a set P of n particles. For every $x_i \in P$ a random location $< x, y, z >$, orientation w and grade g are set where x_i are uniformly distributed over the map.
Result: Estimated Step location and orientation vector : $l =< x, y, z, w >$
for *Each step* **do**
1) Estimated location for each step $< x, y, z, w >$ to *current* (via mobile AR measurement tool)
2) Calculate the step vector $d_i = current - prev$
3) Apply the Move function on all particles in P
4) Apply the sense function on each particle in P
5) Evaluate the weight of each particle according to its new position on the map
6) Re-sample all particles into P'
7) Estimate the current position by calculating the particle's average location in P', considering their weights

end

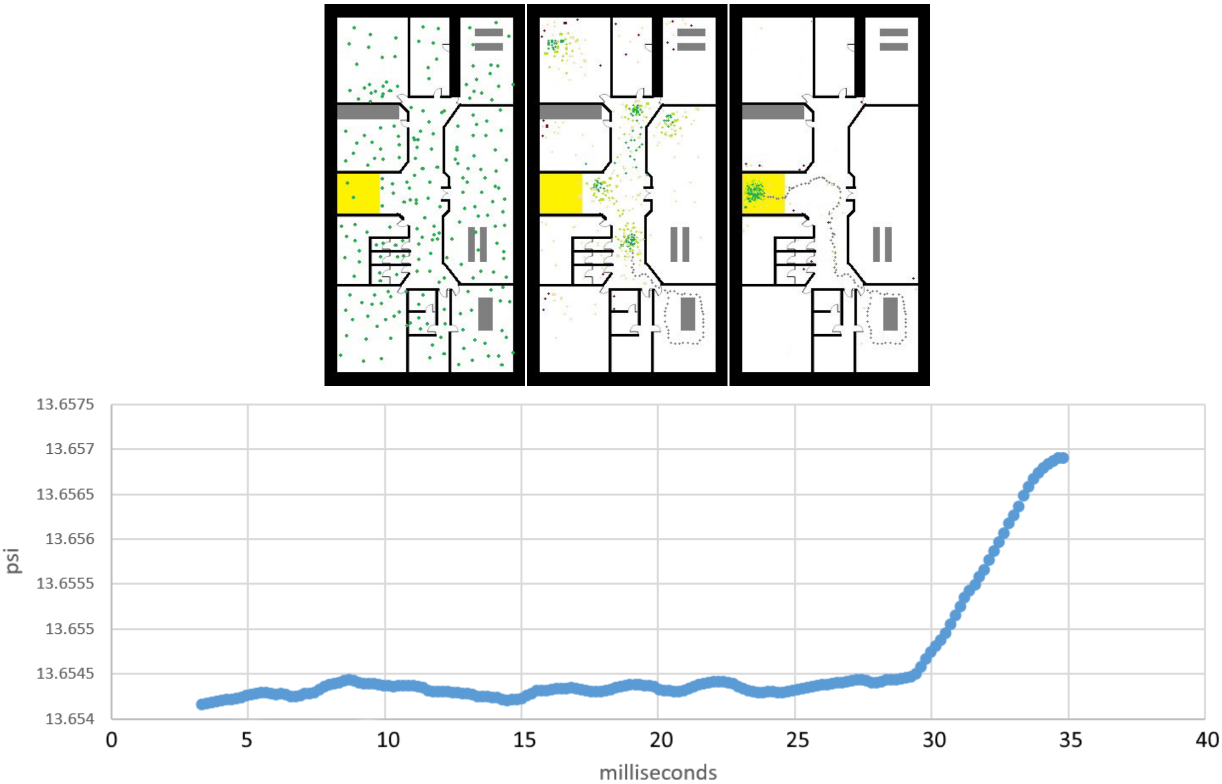

FIGURE 8. Particle filter for localisation. Left: init state, the particles are uniformly distributed. Middle: using the short motion vector the particles are beginning to organise in few clusters. Right: the particles converged to a single position cluster - mainly due to floor change detection. The lower graph shows the barometer raw measurements (in PSI) vs. time. The detection of floor change allowed the algorithm to converge efficiently to the right 3D location.

- Android's Fused Location Provider API: Provides location data based on combined signals from the device sensors using a battery-efficient API. The fused location provider manages the underlying location technologies, such as GNSS, Wi-Fi, BLE, and 4G. The API provides both location and expected accuracy.
- Android Sensor Orientation (Compass): Provides an orientation based on the internal IMU. This API not very accurate and provides no reliable accuracy estimation.
- Google's AR-Core: it is an SDK which provides an API for all of the essential AR features like motion tracking, environmental understanding, and light estimation. We have used the AR-Core for optical tracking. In general the AR-Core tracking has a 1–2% error in 2D at 30 Hz. Such results are significantly better than pedometers, yet, the use of AR-Core raises few issues including: privacy, energy consumption and dealing with the Kidnapped Robot Problem.

3) MITLab TEAM

In contrast with the IPIN 2018 competition, which was held in a shopping mall [9], this year's indoor testing ground has long narrow corridors as well as large halls and cafeterias. The 554 m testing route also passes through outdoor areas like connecting roadways to different buildings, with pauses, loops, closed doors, staircases, and lifts along the way. And Track 1 teams can only use sensors and computation resources on their smartphones.

In order to overcome the challenges where the path covers a vast area, we planned a multi-stage offline training and online inference ensemble learning scheme improved from our previous works [15] as the primary absolute localisation method, and a secondary relative localisation method to refine the localisation results utilizing PDR, based upon another of our previous works [16]. It consists of Data collector; Cloud Server Training, and the Real Time Location System (RTLS) application running on the smartphone.

The Data collector aggregates and processes gathered wireless signal information from partitioned grids of the whole testing area, and sends it to Cloud Servers for offline training and finding the best-optimised parameters for online inference. During the testing phase, the RTLS application running on the smartphones would produce more accurate prediction results based on these parameters. The whole process flow of our primary system is shown in figure 9.

a: DATA COLLECTION AND AGGREGATION

Pruning: Fingerprinting technique relies on finding the best match from gathered fingerprint data sets. In a large testing ground subdivided into many smaller local grids, the feature length of each fingerprint record would impact the performance of our RTLS application running on smartphones.

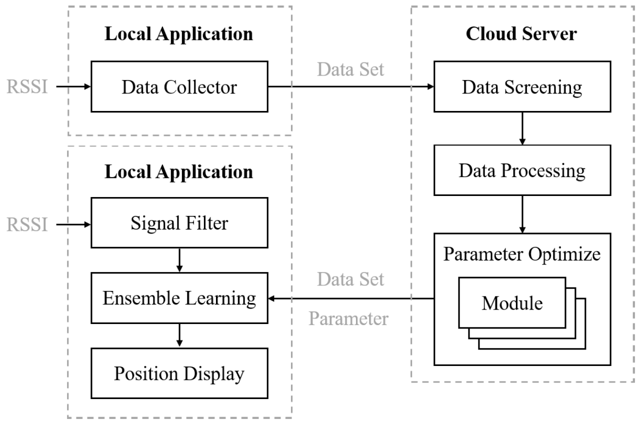

FIGURE 9. System structure.

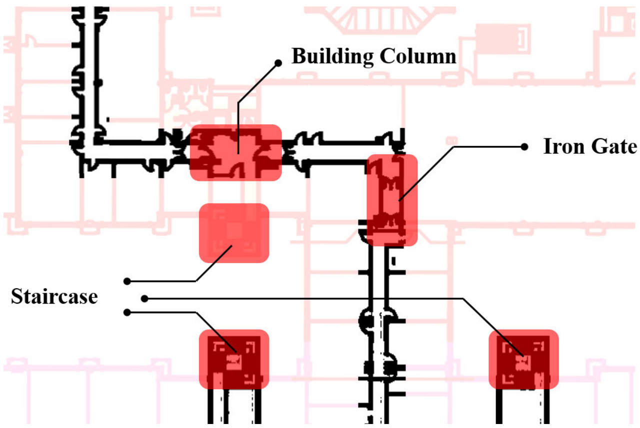

FIGURE 10. Examples of weak signal grids.

To achieve less than a fraction of a second inference time, unstable and weak signal sources were pruned before the data aggregation stage, where only a limited amount of unique and strong stable sources are used as features in the fingerprinting training data set.

Merging and Enriching: Some spots inside small local grids, such as behind metal gates, next to thick building support columns, and especially staircase landing areas, only receive weak and unstable wireless signals or even no signals at all due to large-scale and small-scale signal fading. Hence, additional data collection is required to merge them into the existing data set and enrich it in order for fingerprinting scheme to properly distinguish them. This is where our planned secondary PDR scheme could be of use for identifying nearby grids and as a backup to bind localisation results within certain boundaries [17].

b: DATA WRANGLING

The shadowing effect in a complex indoor environment would cause signal strength to fluctuate locally. The gathered and aggregated data need to be further smoothed and cleaned to improve the prediction outcome. Later on, within the RTLS module, similar data transformation is also performed for more stabled prediction results.

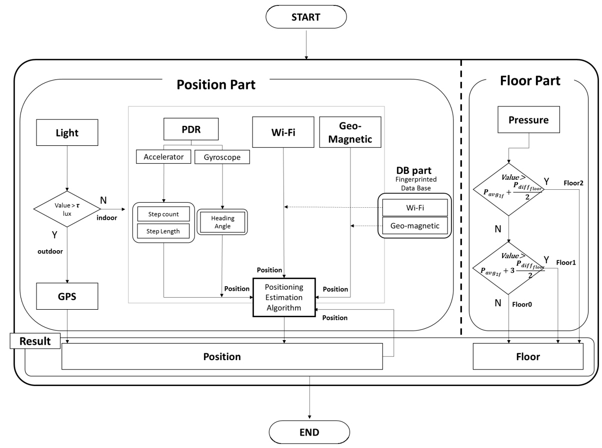

FIGURE 11. Flow chart of the proposed system.

c: HYPERPARAMETER OPTIMISATION

Hyperparameters for machine learning algorithms have a serious impact on prediction and affect our RTLS module inference time and performance. In order to find optimal hyperparameters, training and independently gathered verification data were put through many simulations in our cloud servers. The obtained hyperparameters are sent back and set for the RTLS for testing on smartphones.

4) YNU-MCL TEAM

YNU-MCL is based on a multi-sensor fusion approach where multifarious sensors provide support to enhance the localisation accuracy. The proposed system incorporates the data from a variety of sensors including Wi-Fi, magnetometer, accelerometer, gyroscope, and light sensor. The proposed system is shown in figure 11 . The system is comprised of multiple modules and a brief description of each is given here separately.

a: LIGHT SENSOR (LUXMETER)

The current system makes use of smartphone light sensor to discriminate between indoor and outdoor environments. Since the positioning area for the competition includes both indoor and outdoor space, it is very important to determine the space where the user currently is, as well as the transition from indoor to outdoor and vice versa. This helps in turning on and off the different sensors that are used for indoor and outdoor localisation. For example, when the user moves from outdoors to indoors the GNSS is turned off.

b: PRESSURE SENSOR

The localisation space for the IPIN 2019 Competition is a multifloor indoor space where the path at each floor is different. So the floor detection is important to determine the current position of the user. Although the magnetic field data has been reported to be used for floor detection [18], yet the pressure sensor is a reliable source for floor detection in the short run. Floor detection is performed using the following equations:

$$\begin{cases} P_{val} > P_{avg_{2f}} + \dfrac{P_{diff_{floor}}}{2} & Floor\ 2 \\ P_{val} > P_{avg_{2f}} + 3\dfrac{P_{diff_{floor}}}{2} & Floor\ 1 \end{cases} \tag{5}$$

where P_{val}, and $P_{avg_{2f}}$ represent the current pressure reading and average pressure reading for floor 2 while $P_{diff_{floor}}$ is the difference in pressure measured at various floors.

c: PEDESTRIAN DEAD RECKONING

The PDR part consists of three sub-processes including step detection, step length estimation and heading angle estimation. The data from the gyroscope and accelerometer are used to this end. Step detection is done with the help of an empirical threshold that is used on the accelerometer data. The modified Weinberg model [19] is used for step length estimation as follows:

$$S_l = \sqrt[k]{a_{max} - a_{min}} \tag{6}$$

where a_{max} and a_{min} represent the maximum and minimum acceleration when a step is detected and the value of k is found empirically and may vary with the height of the user.

The current position of the user can be calculated using:

$$x_i = x_{i-1} + S_{l_{i-1}} \times \cos(\psi_{i-1}) \tag{7}$$

$$y_i = y_{i-1} + S_{l_{i-1}} \times \sin(\psi_{i-1}) \tag{8}$$

where ψ represents the heading estimation of the user for the given time.

d: WI-FI AND GEOMAGNETIC POSITIONING

The Wi-Fi and Earth magnetic field data is utilised to determine the current position of the user. Since Wi-Fi requires longer scanning time, periodic Wi-Fi scans are used which can help to make periodic corrections in the current position of the user. The Wi-Fi positioning is based on the enhanced fingerprinting approach proposed in [20] and makes use of multiple features from the fingerprint vector. The magnetic field data are used to calculate the current position of the user. The fingerprinting technique presented in [21] is utilised to build the fingerprint database. The floor information from the floor module helps to load the magnetic database which the user is currently at. Similarly, the position from the PDR module serves to narrow down the search space for the magnetic field database and helps to get a more accurate position. The positioning algorithm gets three positions from PDR, Wi-Fi and geomagnetic modules. Here an extended Kalman filter (EKF) is used to get the current position of the user which is displayed on the smartphone screen.

5) INDORA TEAM

Participating in localisation competitions is beneficial to evaluate proposed solutions, to observe the application in new unfamiliar buildings and to identify key tasks for the further development and research. The core part of our approach is the same as used for IPIN 2018 on-site competition and IPIN 2019 off-site Track. Unfortunately, technical problems were not overcame during the trial, which resulted in unsatisfactory error value. However, a brief analysis of the performance reveals a potential to reduce the output error with the few improvements detailed below.

a: OVERVIEW OF POSITIONING METHOD

The proposed approach consists of Pedestrian Dead Reckoning (PDR), grid-based Bayesian filtering and map model incorporation. The position estimation is updated when a step is detected based on acceleration measurements. PDR method computes a new location estimation related to the current position using a fixed step length and a step heading computed from sensor values.

The floor plans provided before the competition are processed using a custom semi-automatic map editor. The walls and accessible zones are annotated and the map model for each floor is tessellated into a regular grid with a 33 × 33 cm grid cell size. The localisation is performed on a single floor. When a floor transition is detected based on significant changes in barometer measurements, the new map model for the floor is loaded and the localisation process is reset. The initial position on such floor is chosen from a list of all possibilities to enter the floor, i.e., locations of stairs and lifts.

Bayesian filtering technique is applied to reduce the error introduced by noisy sensor measurements and incorrect parameters, e.g., step length estimation. Unlike most researchers and competitors, we do not use Particle or Kalman filter but grid-based Bayes filter [22]. This filter is deterministic discrete implementation of the Bayesian filtering, in which the belief value (probability of the current user location) is computed for fixed points. These points are grid cell centers of the regular grid obtained from the map model. The approach allows to cover the whole map and to use convolution to accelerate the computation but is not able to focus on some areas with higher resolution as Particle filter. In our system, the grid-based filter is implemented in a way that reduces the impact of space discretisation. The belief is computed for the whole grid cell but the position is not always attached to the center of the cell but it is chosen from a list of possible positions within the grid cell (implemented as a new grid layer).

An ad hoc method was added to the system to overcome a problem observed in off-site Track and during competition preparation. The light sensor was used to distinguish between a standard corridor and a balcony hallway which are parallel. The distance between them is a few meters. Therefore, it is possible to select the wrong path when the positioning error increases after a long straight walk. Moreover, a few configurations for centroid grid-based filter and an alternative positioning method were prepared to apply based on the outcome from the first trial.

b: METHOD PERFORMANCE ANALYSIS

The score from the competition (third quartile error 75.3 m) does not describe the true characteristic of the system. The

Android application crashed during all trials and produced only a few first location estimations. For the results computation, the last known estimation is considered as the current location. After the competition, the same experiment with checkpoints was performed by the author with the same device to record raw sensor data for further analysis.

The performance with working application raised the score to 143.8 m. The building with its specifics was quite challenging. We identified main problems and implemented some changes to reduce the output error.

One of the core problem inside this building was caused by incorrect floor detection, even though all transitions were detected and the correct floor was calculated. Our approach finds the closest entry point to the target floor and set the initial position on that floor accordingly. In this building, there are lots of lifts and staircases on a small area which was not the case in the shopping mall at IPIN 2018 or in our scenarios at university in Slovakia. A possible solution is to utilise the Bayesian filtering and to choose not only a single initial location but to assign probabilities (according to the distance from the estimated position) to selected locations representing entries to the floor, e.g., lift doors or a fixed position near staircase. The performance with corrected floor transitions decreased the score from 143.8 m to 38.7 m.

Another issue was the step heading estimation. The computed device orientation was observed drift in some situations. The step heading computation method was modified and simplified a score 33.9 m was achieved with the same configuration as used for the competition. More experiments were performed with different parameters, e.g. step length estimation or orientation variance and the third quartile error was between 30 and 40 m.

Moreover, the path was split into segments formed by consecutive positions on the same floor. Every section was analyzed separately. There were segments with satisfactory score (less than 5 m for all checkpoints) or with error which was observed to be caused by the step heading inaccuracy. However, the longest segment produced a large error compared to other shorter segments. This segment consists of 27 checkpoints and covers the area outside the building, sitting in the cafeteria and the main auditorium visit. Our system was not able to detect the entering in the building from outside, with scores increasing from 17 to 86 m on this segment. Using the light sensor to detect the indoor-outdoor transition decreased the overall score to 22.1 m. After tuning of the step length and other parameters, a score of 16.2 m was obtained. This analysis reveals the main drawbacks of the proposed system with possible solutions for future application.

V. TRACK 2 - VIDEO BASED (ON-SITE)

A. TRACK DESCRIPTION

This competition Track is designed to test state-of-the-art vision-based positioning for pedestrian under realistic navigation environment. It was the second on-site challenge focused on the main use of camera, after the 2018 edition. Track 2 requirements are as follows:

FIGURE 12. Challenging conditions in Track 2: looks similar, Narrow isle, Darkness, Sitting, Reflection, Indoor& Outdoor environments.

- **Hardware:** Competing system should be engineered or implemented in the form of a localisation system that exploits vision sensors (RGB camera, depth camera, or similar devices), except laser based technologies (i.e. Lidar).
  Mobile laptop or tablet PC, smartphone etc. can be used to process the vision data stream.
  An actor carries the competing system, which should be located on the upper part of the body.
- **Operation:** An actor with the organisation wears the competing system and follows the path through the key points. Immediately after completing the path, the competitor submits the log file to the organisers for evaluation.
  Any kind of interaction and data manipulation is not allowed during the trial. Final scores are computed by comparing the position errors between the estimated coordinates and the key point coordinates.

Applied technologies in Track 2 can be summarised with keywords such as *Visual-Inertial Odometry*, *Visual SLAM*, *Visual Landmark Localisation* with the aid of *Deep Neural Network* and *Bayesian Filters*. Several technical challenges were identified during the competition, which were major hurdles for vision-based localisation. Figure 12 shows the situation. The corridors looked similar from all points of view, so it was not easy to extract unique features to be used by computer vision algorithms. Competitors went through several closed doors which caused darkness. Reflection from a vending machine and outdoor sunlight affected the performance of the competing systems.

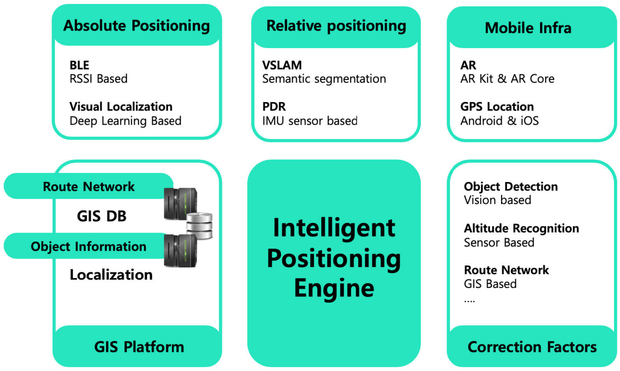

FIGURE 13. Intelligent Positioning Engine.

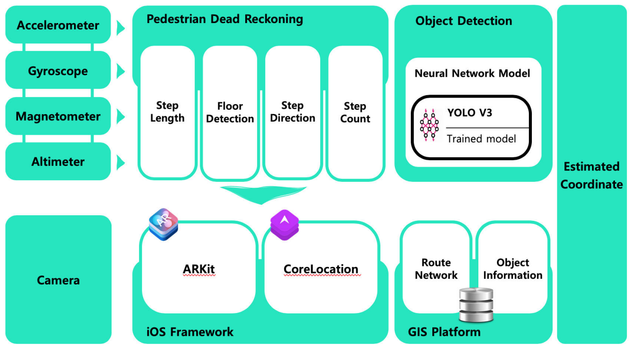

FIGURE 14. System for the competition.

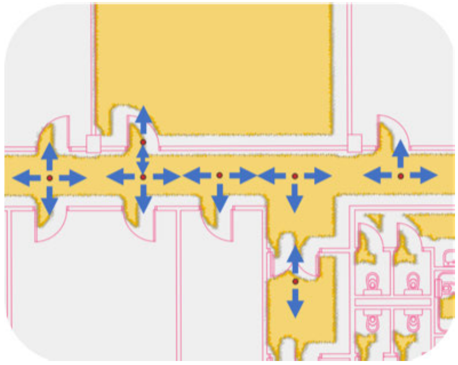

FIGURE 15. Predefined step direction in GIS.

B. INDOOR POSITIONING SOLUTIONS PROVIDED BY COMPETITORS

1) HANA MICRON TEAM

Pedestrian Dead Reckoning(PDR) is a widely used positioning approach. PDR is popular technology of indoor positioning because this technology needs only compact inertial sensor modules such as magnetometer, accelerometer and gyroscope [23]. Most PDR systems are focused on detecting step events by using accelerometer and calculating direction of the pedestrian by using magnetometer and gyroscope to track the current location. Therefore PDR has an advantage over other localisation approaches in that it does not require additional infrastructure.

But PDR is rarely used independently. Since PDR is a relative positioning approach, it needs reference coordinates to track the absolute locations. Also if PDR is working independently then there is no way that we can revise the position when the PDR's cumulative error increases too much. So we need a new technology which provides reliable position to revise PDR's error. One way to adjust inaccurate PDR is using functionality provided by mobile platforms. Apple provides a lot of features that can be used easily. One of them is the iOS native framework, with which we can localise the phone's position and calculate many useful attributes for positioning.

The iOS native framework supports camera position detection and plane detection. It combines a camera and a motion sensor to calculate the relative position in 3D coordinates for what is currently visible and estimates the location of the smartphone. The iPhone's motion sensor is relatively stable in most situations. PDR is vulnerable to sudden posture changes, but the iOS native framework is powerful in that regard. When the pedestrian is not walking, the camera posture is fairly accurate. On the other hand, when the pedestrian starts walking, the step length increases in error. In order to compensate for this, combining camera position with PDR is very important.

Hana Micron Business Development Team has successfully provided mobile indoor navigation service for the stadium at the Pyeong-chang Winter Olympics by indoor positioning technology with integrating BLE beacon, GNSS, Vision and PDR. And we made our *Intelligent Positioning Engine* (see figure 13). It contains our GIS(Geographic Information System). We joined the IPIN 2019 Competition by fusing these positioning approaches.

To meet the requirements of the IPIN Competition, for our entry we designed a simple model as in figure 14 to improve positioning performance with PDR and the iOS framework. It uses a method of inferring the optimal movement trajectory by continuously tracking the attitude of the smartphone with the iOS framework and combining it with the position and orientation estimates from the PDR. Accelerometer, gyroscope and magnetometer are used to operate our PDR and we use the altimeter for detecting floor. Camera is activated for using ARKit which is one of the framework available in iOS. It is implemented in Objective-C on Apple iPhone.

First of all, we adjust step length using ARKit framework. ARKit makes virtual space on the real world using camera and sensors of the smartphone. And we can calculate relative position and vectors of device from this virtual coordinates. By default, our system uses the stride length calculated by the PDR. However, the step length calculated from ARKit is applied to stairs.

Next we use CoreLocation and our GIS to adjust the incorrect step direction. CoreLocation is one of the frameworks available in iOS, such as ARKit. CoreLocation provides GNSS information and general direction of device. And we made up our GIS on the first day. At first, we drew route network on the map, and we predefined information about the direction human can walk. Figure 15 shows the predefined information about a person's direction on the route network. With these two factors, step direction of PDR is being corrected.

We apply object detection to our positioning system. Our approach has three steps. First step is object definition. In this step, we decide which object will be useful in our system. After definition, we collect images of the defined object. And we label the image with what it is. The last step is model training. The training is performed with labeled object images. After training, the model is complete and can use it.

Finally, we are ready for positioning. We get the step length from ARKit or PDR using sensors of smartphone; the corrected step direction is calculated by CoreLocation and GIS; if system detects any object using the camera, then it searches for information on the detected object on our GIS platform and corrects the user location with the position of the detected object.

As a result, we scored a third quartile of error equal to 3.6 m on the competition day. Indoor record is better than outdoor, since more objects which system can detect produce a better result, but there are few objects to detect for correcting position of system outdoors, so it is hard to revise PDR's cumulative error on outdoor.

2) ARIEL TEAM

a: SYSTEM DESCRIPTION

The system was originally designed to be a navigation system for ground robots. The presented navigation framework allows a robust real-time positioning using commercial off-the-shelf sensors. While navigating, the robot is constructing a 3D landmark-map which is used to eliminate sensor drifts. The system is using optical sensors for both tracking and landmark detection, combined with inertial measurement unit (IMU) and ranging sensors; the system requires no calibration in order to report position in global coordinates. The main algorithm is based on a weighted version of a particle filter which uses optical flow-based odometry, map-constraints and deep learning-based optical character recognition (OCR) for landmark mapping. The algorithm is implemented in python and the main two sensors are an Intel Real Sense T265 Tracking Camera and a simple wide-angle camera for landmark detection. Using optical flow and IMU the system's relative 6DoF-path is computed. By combining landmark detection and relative motion, a 3D global map of detected landmarks is computed. Up on having such 3D map the system allows visual navigation by correlating the detected landmarks with those stored in the 3D map. The correlation is being performed using a localisation particle filter – which allows a continuous (∼20 Hz) localisation using visual sensors and an IMU. The system runs on an embedded Linux card such as Raspberry PI4 or Jetson nano and allows 1–5 m accuracy and a relatively robust solution for the Kidnapped Robot Problem.

For the IPIN 2019 Competition the robot navigation system was converted to a handheld one, based on a laptop (Linux OS) which was connected to a tracking camera (Intel Real-Sense T265, which includes an IMU) and an outer

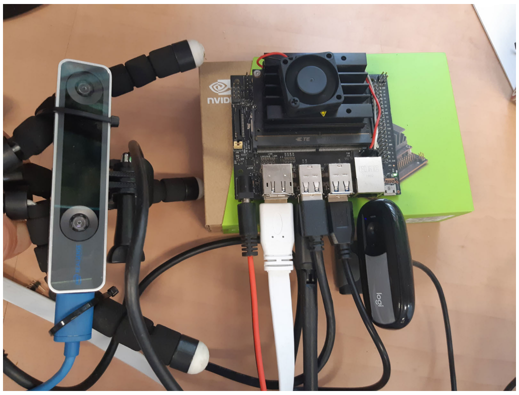

FIGURE 16. The original robotic optical navigation system. This system was converted to a handheld PC-based navigation system in order to participate in the IPIN 2019 Competition.

FIGURE 17. The PC-based optical navigation system used during the competition.

Wi-Ficard for RF fingerprinting localisation, as shown in figure 17.

The navigation method used the landmark (visual) camera due to technical software difficulties. The navigation method used Wi-Fi scans for a global (yet inaccurate) positioning and the tracing camera for refining such position using a map constraint via a particle filter localisation method.

b: PARTICLE FILTER FOR LOCALISATION

The particle filter is as described in subsection IV-B2.d. Here are some additional details about the filter elements.

- **Map:** The particle filter methods estimates the internal state in a given area. Thus, the input of this algorithm is a 3D map of the region, this map should include as many constraints as possible (for example walls and tables). The map constraints are one of the parameters that determines each particle grade as particles with impossible location on the map will be downgraded.
- **Particle:** Particles represent the internal state distribution, so the sum of grades of particles in P is 1 at each step. At the initial step each particle x_i grade is $\frac{1}{|P|}$. The grade of each particle will be set higher as its location on the map seems most likely to represent the internal state.
- **Move function (Action function):** With each step all the particles in the map should be relocated according to the internal movement. Hence, for each step we calculate

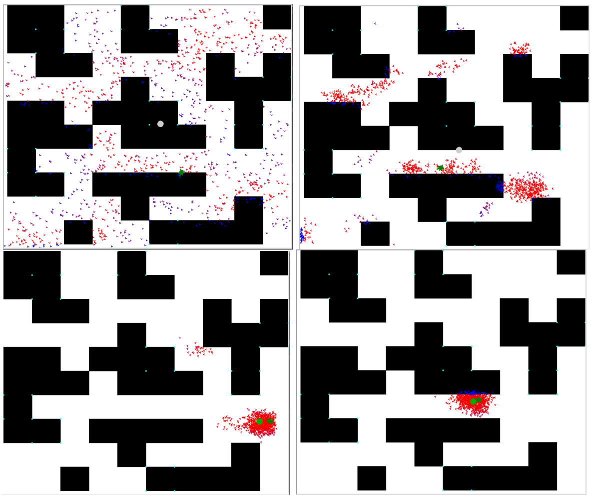

FIGURE 18. The top-left picture shows the initial state of the particles in uniformly distributed state; the next pictures show how the particles are beginning to organise in few clusters. In the last picture the particles converge to a single position cluster.

the movement vector (in 3D) and the difference in orientation, then we move all the particles accordingly. The movement in each step is given by the Tracking Camera T265 which uses the inputs from dual fish eye cameras and from IMU along with processing capabilities in order to provide the host system 6DoF poses.

- **Sense function:** The sensors of the device are also used to determine each particle's grade. The sense method predicts each particle's sense for each step and then grade it with respect to the correlation between the particle prediction and the internal sense. In our case, the sense function can compute the distances to the nearest wall (right and left) and from landmarks that define and then compare it to the distance of each particle to the nearest wall or landmark in the map and change the particle grade according to the correlation.
- **Resampling:** The process of choosing a new set of particles P' from P. The resampling process can be done in several ways but the purpose of this process is mostly to choose the particles with high weight over the low weight ones.
- **Random noise:** Used to prevent particles converging too fast, and by that risk missing the true location. After resampling, we move each particle with a small random noise on the map. Usually this is done by moving each particle in a small radius from its original location.

c: COMPETITION RESULTS - LESSON LEARNED

While testing the navigation system during the IPIN 2019 Competition, we have found that the tracking camera is sensitive to changes in light strength. Thus, few events of major tracking errors accrued while moving from Indoor to Outdoor (on a sunny day). Theses errors were too large for the particle filter to cope with, so while the first 50% of the competition Track the navigation algorithm was able to maintain an accuracy level lower than 2 m, at the 75% of the path the error was exceeding 8 m.

This problem can be partly solved by detecting tracking "jumps" (tracking inconsistencies) and then simply ignore the tracking camera sensors in such cases. Although the overall performance of the system was relatively accurate (third quartile of error was 8.4 m) we argue that, by using more robust tracking capabilities and combining the OCR landmark tracking with the particle filter, one can reach a GNSS-like accuracy in indoor scenarios.

FIGURE 19. Results of the competition.

3) XMU TEAM

a: INTRODUCTION

The accuracy of Wi-Fi positioning is affected by the deployment density, and it is also easy to receive other interfering signals. The use of fingerprints requires a certain amount of collection workload. Geomagnetism uses fingerprint positioning and does not depend on the external environment. It also has the workload to collect fingerprints and poor stability, and the accuracy is low. Inertial navigation positioning is not affected by the external environment, but there is a cumulative error. Visual positioning is susceptible to environmental lighting and other effects, and its stability is average. Our work is to integrate the above positioning algorithms, and in some scenarios use the corresponding good algorithm for correction and short-term replacement, and finally achieve a good positioning effect and improve the overall robustness of the system.

b: SYSTEM STRUCTURE

The system uses IMU sensors to acquire IMU data, barometric data and a camera to acquire real-time images. We get GNSS signals from our Android phone. The VIO system selects the position of the characteristic points as the observation, while the PDR using an inverted pendulum model selects the vertical zero velocity points as the observation. The inverted pendulum model is a simplification of the movement of the lower limbs of the human body, without considering the effects of knee flexion and the feet soles on waist movement. In order to correct the position and attitude deviation caused by the bad quality of observed feature points, the position and attitude of the VIO are replaced by the position and attitude of the PDR to obtain better performance. The image landmark is to judge whether it has come to the calibration

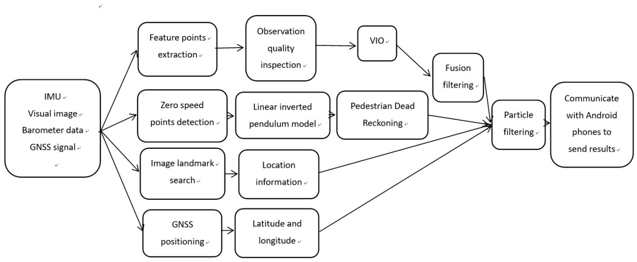

FIGURE 20. Overall framework.

place and obtain the calibration information by comparing the feature points distribution extracted from the real-time image and the off-line image extracted from the landmark database. The particle filter fuses together image landmark location, GNSS location information and walls constraints. The weight of particle distribution is computed according to the quality evaluation of each module, so as to influence the particle distribution and the state of the central particle.

c: CORE PROBLEM

For the evaluation of the quality of the observed feature points of the VIO system, we think that the initialisation error, the uneven distribution, the sparsity, the movement and the mismatch of the features points are factors that affect the quality of observations. Therefore, when these poor quality observations appear, the state quantity may change suddenly. At this time, the state is compensated by using the results of the PDR estimation to eliminate the effect of visual observation errors.

d: CONCLUSION

The system uses the MCKF algorithm and the fusion of multi-source sensors to achieve high-precision indoor positioning in most scenarios, but the positioning results in some extreme environments will be biased, such as in scenarios with few feature points and poor lighting, and there is still space for improvement.

4) KYUSHU UNIVERSITY TEAM

a: GIS-SUPPORTED MAPPING FOR vSLAM-BASED GLOBAL LOCALISATION SYSTEM

We present a global localisation system based on a Geographic Information System(GIS)-supported mapping with visual SLAM(vSLAM) [24]. Our system configuration comprises a monocular camera and a laptop, to a smartphone. In our system, the map of the environment represented in World Geodetic System (WGS84 coordinates) was first generated on the set-up day. Then, the camera was relocalised by using the map on the competition day. The most important task was the generation of a consistent map represented in the single coordinate system. Generally, it is difficult to generate the whole map of a target environment at one shooting due to insufficient visual features at some parts. Therefore, a framework for merging separately-generated maps with reference points generated by GIS software was proposed.

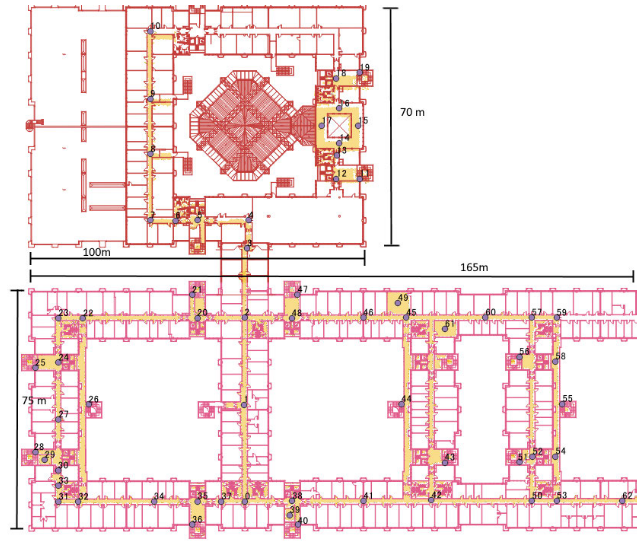

FIGURE 21. Reference points generated on GIS.

b: OVERVIEW

The flow of our framework mainly comprises three steps. The first two steps were performed on the set-up day.

1) Map generation with reference point selection
2) Map merging with reference points
3) Relocalisation and vSLAM for navigation

In the first step, the map is generated by using vSLAM. Our vSLAM implementation is based on monocular SLAM using keyframes and keypoints [25].

First, the target environment is divided into several small areas. Since the passages were narrow at the competition site, keypoint tracking in vSLAM often failed at the corners due large orientation changes. Therefore, vSLAM was performed for each straight passage.

As illustrated in figure 21, we manually generated reference points where longitude and latitude are known by using GIS software.[3] While performing vSLAM, the camera poses at reference points were interactively recorded, as reference point selection.

In the second step, the coordinate system of each map is merged by using the reference points because each map is represented in an unknown individual vSLAM coordinate system. First, the origin of each coordinate system was shifted to one of the reference points in each map. Then, the scale and the rotation of the coordinate system were unified by using the longitude and latitude of the reference points. Optimisation was performed using a cost function. Finally, the maps were merged by shifting the origin of each coordinate system into WGS84.

In the third step, relocalisation was applied using vSLAM on the competition day. When the competition path was outside of the map generated on the set-up day, the mapping was performed for continuous localisation.

[3]https://www.qgis.org

c: RESULT

The difference between the competition path and our path for mapping is presented in [24]. Unfortunately, there was no overlap between them. The most difficult issue was the limited time for preparation. In this competition, the large site comprised many texture-less and dark locations. The same passage was captured several times because vSLAM often failed. In addition, battery life was a practical issue. Since vSLAM needs significant computational resources, the battery was drained in about 30 minutes for the laptop. Therefore, it was difficult to generate the whole map within a few hours.

Generally, a large-scale navigation system cannot be realised by using a camera only because vSLAM fails when visual features are not detected, as we witnessed. Therefore, sensor fusion with Wi-Fi or 2D map-matching should be incorporated for a system to be stable. Also, map generation for a large-scale environment needs to be simplified for fast set-up.

VI. TRACK 3 - SMARTPHONE-BASED (OFF-SITE)

A. TRACK DESCRIPTION

The third Track is devoted to evaluating smartphone-based location technologies in an *off-site* context. For that purpose, data was collected while walking through the competition area for training, validation and evaluation purposes. This Track follows the same data collection and evaluation strategies of the off-site competitions organised in previous years [9], [26], [27].

The competition area was visually inspected to identify the most challenging parts of the research campus for the off-site evaluation and the key points needed for the competition were selected. In contrast to the IPIN 2018 Competition, a Wi-Fi coverage analysis was not done as the local organisers already knew that it was good enough inside the facilities. As done in the previous competitions, the data provided to the competitors was collected using the Android app "GetSensorData" [28]. This app automatically gathers data from a smartphone sensors and allows manually adding user-defined positions. Key points were added to all collected data sets. Data was collected in three independent phases: training, validation and evaluation.

For the three phases, we used a Samsung Galaxy A5 2017 (SM-A520F) phone with Android 8.0. We set the maximum sampling rate allowed by each sensor as shown in table 2. The sampling frequency of the Wi-Fi sensor depends on the connection status. If it is not connected to any Wi-Fi network, its sampling frequency is around 0.22 Hz (sampling interval of around 4.5 s). However, we detected that it dropped to 0.16 Hz (sampling interval of approximately 6 s) when the phone was connected to a Wi-Fi network. Therefore, we configured the smartphone to prevent it from connecting to Wi-Fi networks during the data collection. The GNSS data only provides an estimation of the global coordinates in WGS84 provided by the GNSS sensor and the network information.

TABLE 2. Information of the sensors in the Samsung Galaxy A5 2017 (SM-A520F).

Sensor	Model & Manufacturer	Sampling Freq. (Hz)
Accelerometer	STM - K6DS3TR	200
Gyroscope	STM - K6DS3TR	200
Magnetometer	AKM - AK9916	100
Barometer	STM - LPS25H	5
Light Sensor	AMS - TMD3725	5
Proximity Sensor	AMS - TMD3725	2
AHRS	Samsung	100
GNSS	GNSS/Network	N/A
Wi-Fi		≈0.2
Sound		2

A future versions of "GetSensorData" will be able to collect raw GNSS data. The indoor positioning community is invited to suggest changes, add new features and, in general, improve this data collection tool [28].

For the training phase, the Track chairs defined 10 short trajectories in the area to record the required data. Key points were recorded at every significant turn, so lines connecting intermediate points were representative of the trajectory done and competitors can assume that the trajectory between two points was almost rectilinear. All those trajectories did not contain any floor transition. Additionally, Track chairs also collected specific data at five floor transition zones, i.e. the stairs. All the trajectories were collected 4 times and in both walking directions. Regular training data at corridors was collected from 27 March at 13:00 until 28 March at 11:00. Training data in floor transition zones were collected on 28 March from 11:00 to 14:00.

For the validation phase, Track chairs defined slightly more complex trajectories. The number of key points was also lower and Track chairs did not guarantee that every significant turn was manually marked with a user-defined position. Thus lines connecting intermediate points were not representative of the trajectory done and competitors cannot assume a rectilinear trajectory between two consecutive points. Moreover, those trajectories could be multi-floor. The trajectories were collected just one time in a single walking direction. Validation data was collected on 28 March from 14:20 to 17:20.

Training data is usually used as a reference for the IPS, whereas validation data can be used by the teams to estimate the accuracy of the developed solution. Validation data is also useful to select the most appropriate parameters of the IPS if they are independent of training data. To participate in the competition, competitors could use both data sets at their own discretion. In fact, competitors could also use data sets provided in previous editions or new data sets collected in their own facilities to perform calibration and internal validation. However, competitors could not collect additional data in the evaluation area.

Finally, a long path covering all the evaluation area was recorded with the app for the evaluation phase on 29 March in the morning, resulting in a blind evaluation log file without any reference key points, lasting more than 20 min. This data set and supplementary materials –e.g. floor-plans– were provided to competitors for Track 3 evaluation. These contents and the ground truth location for evaluation are now available for further benchmarking in [29]. This package complements the ones from the previous editions [30]–[32].

B. INDOOR POSITIONING SOLUTIONS PROVIDED BY COMPETITORS

1) INTEL LABS TEAM

Intel Labs has studied a positioning technique that relies on Wi-Fi ranging and built-in sensors of mobile devices. A benefit of the range-based approach is that a ranging strategy can be adaptively optimized for each indoor environment without collecting any ground truth data. For instance, every trainable parameter related to the ranging process can be optimized using wireless data accumulated when users use a positioning application [33], [34] or extra sensor data generated inside mobile devices [35]. By doing so, the time and effort required to deploy and calibrate positioning solutions can be significantly reduced. The performance of the range-based technique has been verified with various ranging sources, including round trip time (RTT) measurement using the fine timing measurement (FTM) protocol defined in the IEEE 802.11-2016 standard [33], [34] and the channel state information (CSI) of beacon frames [35].

One of the biggest challenges for this team to participate in the competition was that the provided training data do not include the coordinates of Wi-Fi access points, which are essential for range-based positioning solutions. Even though an automated way to acquire the coordinates of access points was studied in [36], this technique could not be applied for this competition as it needs to know the coordinates of a few access points as a reference. For this reason, the Wi-Fi fingerprinting technique was used instead of the range-based approach.

Figure 22 illustrates the block diagram of the proposed approach, which consists of three stages: the Wi-Fi fingerprinting, PDR, and trajectory fusion. The proposed approach uses the Wi-Fi fingerprinting and PDR techniques to separately estimate the trajectory of the device, and fuses the two estimated trajectories to produce precise trajectory. In addition, the current floor is detected primarily relying on air pressure measurements. The details of each stages are described as follows.

In the Wi-Fi fingerprinting stage, the training data are used to create a radio map for each floor using received signal strength (RSS) measurements. For simplicity, only RSS measurements in the 2.4 GHz frequency band were considered. While investigating the provided training data, it was found that some access points broadcast multiple service set identifiers (SSIDs) at the same time. Therefore, multiple MAC addresses that are likely to come from the same access point were consolidated into one to avoid duplication. In addition to RSS measurements, the training/test data also provide GNSS coordinates of the device. Therefore, these data were partially

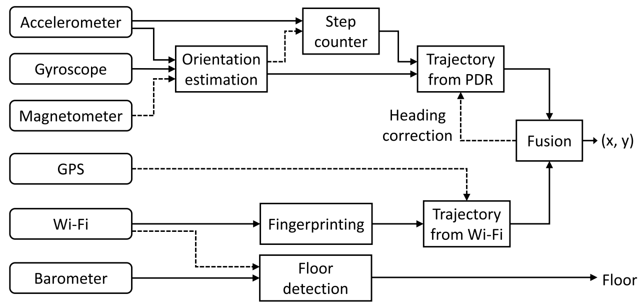

FIGURE 22. Block diagram of the proposed approach based on Wi-Fi fingerprinting and PDR techniques.

used when the Wi-Fi fingerprinting technique can not provide precise position estimates, for instance, if there are only few access points available.

In the PDR stage, the orientation of the device is estimated using accelerometer and gyroscope readings. The magnetometer was rarely used in this competition due to the distortion of the magnetic field. Using the estimated orientation of the device, the local accelerometer readings can be transformed relative to the reference coordinates system. Among the transformed values, the z-axis component is used to estimate the traveled distance of the device by capturing the vertical movement pattern of the device, which is generated when the user walks. In addition, the heading direction of the device is also obtained from the estimated orientation of the device, and thus, the trajectory of the device is obtained by combining the traveled distance and heading direction. The details of the PDR technique are introduced in [34].

Finally, the fusion stage combines the two separately estimated trajectories to produce an accurate trajectory. Because heading estimation is the most critical factor that impacts the accuracy of the PDR technique, this stage periodically corrects the heading direction using the fingerprinting results. One problem is that there is a delay of a few seconds between the Wi-Fi and sensor measurements. When performing a Wi-Fi scan operation, the Android system typically allocates 100 ms for each Wi-Fi channel and reports the scan results after finishing the entire scan procedure. Therefore, the scan results for the 2.4 GHz band, which are used at the Wi-Fi fingerprinting stage, are actually 3–4 seconds delayed information as the Android system scans around 30 Wi-Fi channels in the 5 GHz band. Such delays were carefully corrected in the fusion stage.

2) NAVER LABS EUROPE TEAM

Our objective is to obtain a reliable prediction of the trajectory of a user from the data collected by his/her smartphone, using inertial sensors such as the accelerometer and the gyroscope, as well as other type of sensors such as barometer and Wi-Fi scanner. Our system is based on four main components:

- A deep learning-based pedestrian dead reckoning (deep PDR) model that provides a high-rate estimation of the relative position of the user.

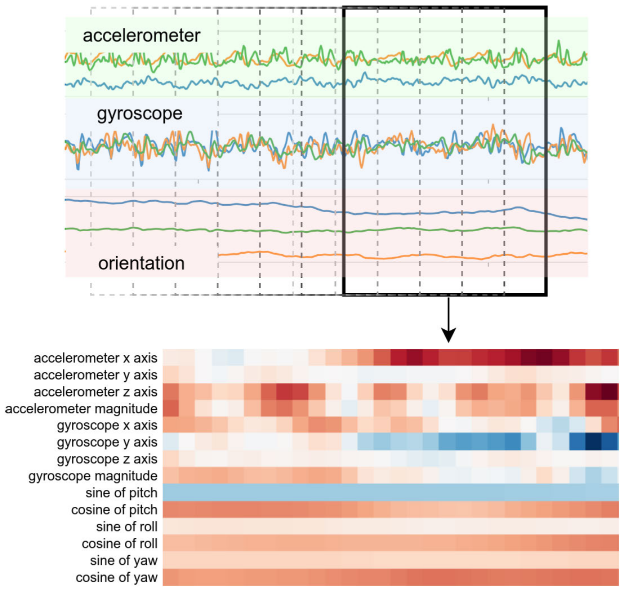

FIGURE 23. **Feature extraction for deep PDR.**

- An indoor location system based on Wi-Fi fingerprinting that provides a prediction of the user's absolute position each time a Wi-Fi scan is received.
- A fusion of the two above-mentioned predictions using a Kalman filter. The output of this component is a new estimation of the user's global position.
- A structural projection method that takes into account the physical constraints of the environment (corridors, doors, etc.) and projects the prediction from the Kalman filter on the possible paths.

a: DEEP PDR

Classical PDR techniques infer speed of a user through steps detection, extracted typically from accelerometer and orientation sensors, and an approximation of the user's step length. The error of the PDR estimations is usually caused by both heading and step length error. The stride of the user does not have to be constant and depends, among other factors, on the physical characteristics of the user.

Deep learning finds features and classification boundaries through optimizing a certain loss function, employing a deep neural network architecture. Convolutional neural networks (CNNs) have achieved state-of-the-art results in image recognition tasks, where the nearby pixels typically have strong relationships with each other. Stacked convolutional and pooling layers act as a hierarchical feature extractor.

Although CNNs have been mostly used for computer vision tasks, we believe they can efficiently capture local temporal dependencies of motion signals and should be able to identify multi-modal correlations among sensors. In multimodal approaches, where many sensors are used to characterise a movement, correlations among distinct type of sensors may also have an impact on the correct interpretation of data. CNNs can exploit the local dependency characteristics inherent to time-series sensor data and the translation invariant nature of movement.

A temporal window of inertial sensor data can be associated to its corresponding change in the user's position. Temporal and multimodal correlations present in the sensory data can be learned using a supervised deep learning approach to predict the associated displacement, training a deep neural network to predict the relative change of position associated to a series of sensor data represented by a sliding window over the accelerometer, gyroscope and orientation readings (see figure 23). Using this approach, the inertial sensors' readings are used to predict short term displacements of the user. Gyroscope measurements allow us to detect changes in orientation and can also be used to filter heading to get a smoother trajectory.

All the data contained in the training and validation sets are used to train the deep learning model that will be responsible for predicting the user's trajectory based on the inertial sensor data, replacing the classic PDR method.

b: WI-FI: PREDICTIONS WITH K-NN

To obtain an absolute position reference, we build a radio map using available Wi-Fi RSS data. We interpolate the position at which a fingerprint is received, assuming the user is moving at a constant pace, and using accelerometer data to detect static and movement intervals. Once the radio map is built, the user position can be predicted using classical machine learning algorithms such as k-NN or SVR.

c: KALMAN FILTER FOR FUSION

The observations of the user state obtained through the previous methods are integrated using a Kalman filter (KF). The KF output provides reliable estimates of the user's position based on a sequence of inaccurate inputs. The filter outputs the corrected path using absolute position estimations from the Wi-Fi positioning system and the relative estimations from the deep PDR model.

d: STRUCTURAL PROJECTION

The KF does not take into account physical constraints imposed by the floor layout. Meanwhile, the predicted trajectory can not go through walls, changes of floor can only occur at stairs, etc. Therefore, we proposed a method that adjusts the KF output and projects it in the accessible paths only, these paths are extracted from the training and validation data.

3) IOT2US TEAM

The processing workflow has four main steps. 1) Floor level determination. 2) Motion pattern detection and sub-trajectories segmentation 3) Sub-trajectory reconstruction and track optimisation. 4) Track result re-sampling. Time series data from seven types of smartphone sensor were fused to reconstruct the track; each step only making use of some of them, as shown in figure 24. Additionally, map information was matched to the tracks for optimisation in step three.

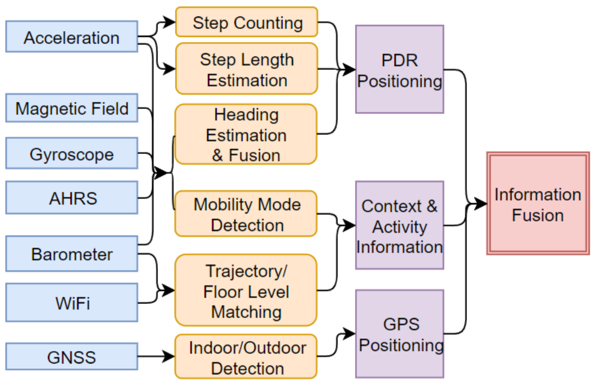

FIGURE 24. Smartphone Sensor Data Fusion.

a: STEP 1

In the first step, the determination of the floor level is based on the PRES data from the barometer and Wi-Fi data collected from known Wi-Fi APs. The process does not require complicated online matching but simply makes use of existing MAC address list to determine the floor ID level and stairs ID [37]. However, since the Wi-Fi data is collected with a frequency of approximately 0.25 Hz, it cannot provide enough time resolution to determine the precise start and end points of transitions between floors. Therefore, PRES data, which was collected at a higher frequency of 5 Hz was used to detect the up or down stair motion. A Gaussian filter was used to smooth the data before calculating the gradient of motion. Then, the start and end of the transition between floors can be clearly identified. Training data set was used to tune the parameters in this process. Also, Wi-Fi data matching the training data set of floor transitions can determine the coordinates of the transition location.

b: STEP 2

In step two, different motion modes can be detected using machine learning or deep learning algorithms operating on the multi-sensor data. Six categories of motion were defined: walking, turning, stationary, ascending (stairs), descending (stairs) and irregular movement. Our processing workflow included data segmentation, labelling, feature extraction and classification. We made use of accelerator, gyroscope, magnetic field, AHRS and pressure data for motion mode classification. Some recognizable statistical characteristics (e.g. mean, maximum, derivative) of these time series in the time-domain are extracted as features. Decision tree and support vector machine (SVM) were investigated to classify these motion modes.

Turning points and walking episodes are combined to segment the trajectory in time while the location of the segmented sub-trajectory is determined by Wi-Fi fingerprinting algorithms. Note that due to the low data collection frequency of Wi-Fi, we do not use the Wi-Fi data to estimate the trajectory but use it to match the sub-trajectory with the Wi-Fi fingerprint database to find an approximate location. The positions of reference points provided in the training data set is also recorded as important known knowledge for the following step.

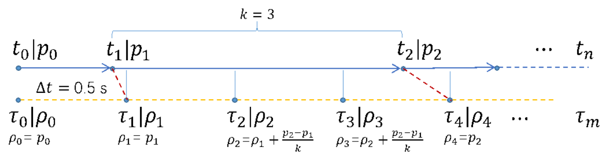

FIGURE 25. Re-sampling Process.

c: STEP 3

In this step, a PDR algorithm is applied to reconstruct the detailed segmented trajectory coordinates with time stamps. Also, all the parameters required by the PDR were determined in step two where we identified the step length, step detection threshold, etc. Moreover, known knowledge of the map can also be used for trajectory optimisation. Since each segmented sub-trajectory can be matched to a known position, then the start and end points of each sub-trajectory can be used for the optimisation of the trajectories estimated by PDR.

A special case occurs when the GNSS data is also available, where there is a strong possibility that the trajectory is outdoors in an open space. In this case, the map information is not sufficient to support the trajectory optimisation as there is no clear corridor or room structure restriction. Hence, we used a fusion of the PDR and GNSS methods to optimise the sub-trajectories. A Kalman filter was applied in this process in which we take the PDR results as the observation model and the GNSS results as the execution model.

After the sub-trajectory reconstruction process, the optimisation work is mainly focused on the heading estimation adjustment. As in most cases of turning motion, it happens at corridor corner where we already knew the coordinates and angle of it. Then the deviation of heading which estimated from AHRS data can be corrected with map matching.

d: STEP 4

In the final step, all optimised sub-trajectories are concatenated chronologically. Due to adjustments applied in step three, the coordinates of the end point of one sub-trajectory and coordinates of the start of the following sub-trajectory may have a gap or an overlap. We let the track data re-sampling smooth these gaps and also generated the final answer in the required time slot (0.5 s). The resampling process is illustrated in figure 24, where t_n is the time slot we want and p_n is each t_n corresponding position (coordinates), which are the results calculated in the previous steps. τ_n and ρ_n are corresponding time points and positions which are the desired results in the desired time slots. k is the number of sampling points between two t points.

4) AraraDS TEAM

AraraIPS is Arara's proprietary indoor positioning technology. Arara is engaged in developing advanced knowledge

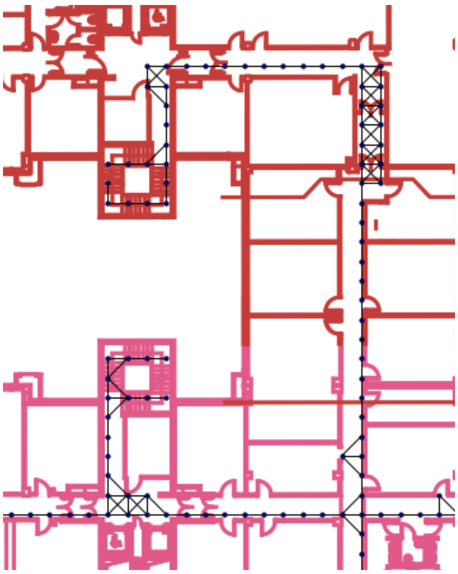

FIGURE 26. Sample portion of the graph representing the venue.

solutions and producing high-quality technology to address modern business and industry challenges. AraraIPS has been one of the central issues in our research agenda for the last three years. It is a functional indoor positioning system offering several commercial solutions as of today.

Our system's approach to indoor positioning has four distinctive characteristics: it is based on a cartographic paradigm (fingerprinting), it uses a discretisation of the predicted floor/building, it is measurement-agnostic (i.e. its abstract formulation is not specific to any kind of signal or measurement such as Wi-Fi, magnetic field, BLE, etc.), and it exploits measurement history. Let us have a closer look into each of these features as we get a better feel of how AraraIPS works.

Fingerprinting has become a relevant technique in indoor positioning approaches. The reason is that alternative, range-based techniques are based upon trilateration or triangulation, in which sufficient geometric information (with respect to reference landmarks) singles out the position of the object to be located. These methods are based on underlying hypotheses (e.g. clear line of sight between object and reference landmark is needed to establish a functional one-to-one relation between distance and signal intensity) which usually do not hold in the dynamic, cluttered context of indoor spaces.

Our system also relies on the discretisation of the underlying indoor space. In practice, this means that a graph is built from the map of a venue, in which nodes are possible locations where the tracked device can be found and edges connect neighboring nodes. This effectively turns the positioning problem into a classification one, in which the prediction is one of finitely many possible locations. It has the further advantage of ruling out inaccessible locations (e.g. walls) and thus not complicating the prediction task unnecessarily.

The final ingredient in our system is to enrich the information available to the prediction module by taking into account the history of measurements, exploiting the fact that measurements taken close in time will be strongly correlated. Thus, we expect the prediction to narrow in on the true position with greater and greater confidence as time goes by. The mathematical formulation of this idea is that of a random walk on the graph of the venue, in which transition probabilities at a given instant in time depend on the measurements taken at that particular time. This dependence is made precise by our underlying measurement and node transition probabilistic models, which we choose not to disclose.

5) UMinho TEAM

The UMinho team adopted a two-phases approach based on a combination of Wi-Fi fingerprinting with data from other sensors. In the first phase, a radio map was built using the Training data sets. In the second phase, the Evaluation trajectory was estimated by fusing position estimates obtained from Wi-Fi fingerprinting with data from other sensors, as described below. Validation data sets were used to evaluate the performance before the competition.

a: BUILDING THE WI-FI RADIO MAP

The provided Training and Validation data sets are similar in the sense that they both include similar data from the sensors and also some ground truth points (POSI records). Additionally, Training data is described as representing a set of trajectories where the path between consecutive ground truth points is along a straight line, except for those collected while using stairs. Since Wi-Fi samples do not include the position where they have been collected, those positions must be estimated. The solution to this problem was based on estimating the trajectory between consecutive ground truth points using PDR (module 1, figure 27). Step Detection (SD) and Step Length (SL) estimation were performed by processing data from the accelerometer (ACCE records). For the Regular Training data sets, a straight line was assumed between consecutive ground truth point, thus defining the heading. For the Validation data sets, the trajectories between consecutive ground truth points were estimated using SD and SL estimations, and the heading (yaw) included in the AHRS records. In both cases, the heading and SL estimates were adjusted so that the estimated trajectory matched the ground truth points, as illustrated in figure 28.

Wi-Fi samples were then assigned a position along the estimated trajectories through linear interpolation using the sensor timestamps. A floor and z coordinate were assigned to each Wi-Fi sample using POSI data and by processing data from the pressure sensors (PRES) (module 2).

b: ESTIMATING THE FINAL TRAJECTORY

Figure 27 provides an overview of the system used to estimate the final trajectory from the Evaluation dataset.

As in the first phase, ACCE data was used for SD and SL estimation that, together with heading information from the AHRS records, were used to estimate an initial trajectory using PDR (module 3). Of particular interest is the displacement between consecutive steps.

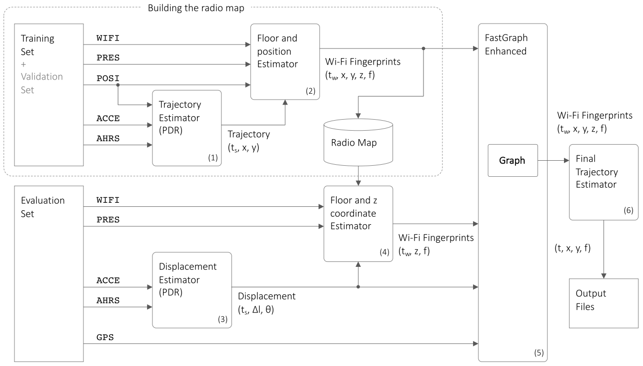

FIGURE 27. Overview of the adopted approach.

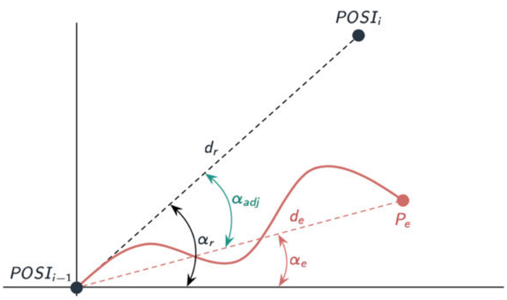

FIGURE 28. Estimating the trajectory between consecutive ground truth points: heading and step length were adjusted between any two POSI records.

Each Wi-Fi sample was then assigned a floor and z coordinate estimates using fingerprinting (k-NN) and pressure data (module 4). Pressure data was particularly useful to estimate the z coordinate while changing floors, while fingerprinting is more robust in estimating the absolute floor.

A variation of the FastGraph Enhanced algorithm [38] was then used to estimate the position of each Wi-Fi sample (module 5). In this version, the graph was initialised using the radio map built in the first phase, instead of using data from fixed Anchors. Then, each new Wi-Fi sample (Evaluation) was added to the graph using the constraints defined by the floor and z coordinates estimated in module 4, and displacement information estimated in module 3. The GNSS observations with higher accuracy were integrated into the graph as additional nodes, adding new constraints. These were important to estimate the initial and final positions of the trajectory, as well as other parts of the trajectory that took place outdoors. The final trajectory was built, and represented in the required format, through linear interpolation using the timestamps of the Wi-Fi and GNSS records.

c: PRE-COMPETITION EVALUATION

Before the competition, the developed solution was evaluated using only Training data to build the radio map and by plotting the trajectories estimated for each one of the Validation paths. The error was evaluated by measuring the positioning error at the provided ground truth points (POSI records in the Validation datasets). This evaluation revealed that the main errors were observed in parts of the trajectory where there is a significant disturbance in the heading information obtained from the AHRS records. A summary of the obtained results for each Validation trajectory is shown in table 3. Floor estimation was 100% correct for all data sets.

d: POST-COMPETITION EVALUATION

The third quartile of the position error metric achieved by the UMinho team was of 3.0 m (mean error of 2.4 m). This result is much better than those obtained for the Validation data. However, it must be noted that Validation performance analysis was done using just a few ground truth points (the POSI records) that were typically placed at the end of corridors, and not along with them. An evaluation of the adopted solution was performed after the competition using the ground truth data provided by the competition organisers. As before, the larger errors were found to be associated with the disturbances observed in the AHRS data (heading), suggesting that further work is needed to improve heading estimation.

6) UGent TEAM

The core of our location tracking system is a route mapping filter [39] that is based on a motion model and the Viterbi principle, a technique related to Hidden Markov Models and backward belief propagation. The physical layout of a building is used to construct the most likely path instead of a sequence of independent, instantaneous estimates. This post-processing filter ensures physically realistic trajectories and has been shown by independent researchers to outperform traditional approaches such as smoothing particle filters [40]. During initialisation, the route mapping filter starts with N paths (e.g., 1000 starting points) that are located in a circle around the best first estimation given the first Wi-Fi measurements and an RSS fingerprint map based on the training data [39]. These N paths are updated each time new Wi-Fi measurements become available. The next candidate positions, starting from the current last points of the paths in memory, are determined based on a maximum walking speed (derived from a step counting algorithm using the available accelerometer data), and the walls and obstacles of the building (people cannot move through walls). Each path consists of a chain of grid points and a cost that indicates the probability of this path at this time step. The path with the lowest cost after processing all sensor data is the most likely trajectory. The cost of a path is the sum of costs based on various sensor measurements: Wi-Fi RSS measurements, magnetometer, barometer, accelerometer and gyroscope data.

Wi-Fi: the RSS values are compared to the corresponding reference values in a RSS fingerprint map and are weighed based on the estimated distance to the Wi-Fi access points. The fingerprint map itself is based on all training data, grouped per BSSID and per grid point.

Magnetometer: the magnetic field values are compared with the corresponding reference values in a magnetic fingerprint map. The fingerprint map itself is based on all training

TABLE 3. Validation Results (meters).

Validation Set	Mean Error [m]	Median Error [m]	75^{th} perc. [m]	90^{th} perc. [m]
v01	4.0	4.0	5.5	6.7
v02	2.8	3.2	3.5	3.9
v03	2.6	2.3	3.6	4.6
v04	3.2	2.2	4.1	7.3
v05	4.3	3.8	4.9	7.5
v06	4.4	3.4	4.3	9.9
v07	2.9	2.7	3.8	4.2
v08	3.4	2.4	4.3	7.5
v09	2.3	1.9	3.6	4.5
all (mean)	3.3	2.9	4.2	6.2

data, grouped per grid point and orientation. The closest neighbor is used when a path visits a grid point without any reference measurements (both for Wi-Fi and magnetometer).

Barometer: the differences between the average pressure over a short (5 s) and a long window (30 s) are used to detect up or down floor changes when the difference exceeds a certain threshold based on the training data. Furthermore, a cooling-off period is implemented to avoid changing floors multiple times within a short time span. Paths that do no change their current floor in the right direction (by taking the escalator or lift) get an additional cost assigned, e.g., 15 m.

Accelerometer, gyroscope, and mobile phone 3D orientation: these data are fused together and used to detect the step count, stride length and orientation between two locations updates; combination of these three gives us the traveled distance and direction. The difference between this traveled distance and direction, and the distance and direction between a grid point and his parent grid point (i.e., the previous grid point of the path) are used as an additional cost. This penalties paths that move when the accelerometer and gyroscope estimate that the user is standing still and the other way around when a path remains static and the user is moving or when a path takes a turn in the opposite direction.

The physical layout of the building is modeled by a shapefile, constructed with QGIS, the PDF maps with georeferenced points, and a plugin to reference the raster to the projected coordinate system by creating a GeoTIFF file. Each floor is represented by a polygon with the floor id as a feature value and likewise, the escalator and lift are represented by a polygon with the start and end floor as a feature value. The route mapping filter uses this shapefile as input to construct a grid database with a certain grid size, e.g., 1 m, and a reachable database, consisting of the reachable grid points, for each grid point. The reachable grid points are the neighboring grid points that do not cross walls or obstacles, and the above or below grid points if it is located within the polygon of an escalator or lift (and correct floor level). This grid and reachable database are used to select the next candidate positions in the route mapping filter, given the current last points of the paths in memory and the time that has passed since the last location update.

a: LESSONS LEARNED

We assigned too much weight to the Wi-Fi and magnetic measurements in the cost function of our algorithm. This caused the reconstructions to be mapped to areas for which RSS and magnetic training data were available, which is disadvantageous for an evaluation that contains previously unvisited places. It would be better to assign more weight or make a switch to a pedestrian dead reckoning technique when the best matches between measurements and the fingerprint databases become too large. The competition is a well-organised event and a useful contribution for the indoor positioning and tracking community.

7) INDORA TEAM

The main goal for the participation in the off-site competition Track was to evaluate the same localisation method as used for various experiments and on-site competitions (e.g., IPIN 2018 competition [9]). Multiple system configurations were chosen to produce position estimations. However, no postprocessing or any changes to the output were applied. The expectation was that the off-site results would show the real performance of proposed methods. Another goal is to overcome implementation problems and find the system configuration such that the live positioning error would be at the same level as this value.

a: POSITIONING METHOD OVERVIEW

The method is the same as that used in Track 1 on-site competition described in section IV-B5.

For the off-site competition, the measurements file was split using floor detection method and the location estimations were calculated separately for every floor. The initial location for the ground floor was determined from GNSS measurements. Initial positions for every following floor were chosen from a list of possible places, i.e., lift doors or entrances to staircases.

The absence of ground truth positions requires alternative methods to evaluate the estimated path. Visual analysis of the path supported by some statistical values for the estimations may be used to rank the positioning attempt. Visualization of detected steps with proper directions provides an insight into the real path covered by the measurements. Comparison of

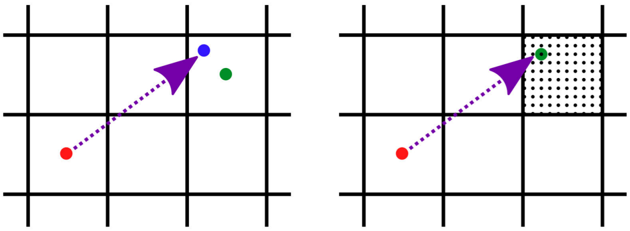

FIGURE 29. A step performed from the red point to the blue point on the left figure. The source position for the next step is labeled with the green point. The distance between the blue and the green point increases the localisation score. Centroid grid-based approach introduces another grid layer and reduces the error in such situations by choosing the estimated positions from a set of points on the fine grid.

such visualizations on the map with different configurations allows to determine the expected step length and transition locations between floors.

b: CENTROID GRID-BASED BAYESIAN FILTERING

The component with the main research focus of the introduced localisation system is the grid-based implementation of Bayesian filtering [22]. Unlike widely used Particle filter, the grid-based approach is deterministic. The full map is covered by the grid and the belief value is calculated for every grid cell. One of the main drawbacks of such solution is the computational complexity. Any grid-based method used for real time localisation should define a low-dimensional state with convenient grid cell size. In this approach, only two-dimensional position is represented by a single grid cell. The selected cell size defines the precision of the estimation. Therefore, it is not possible to increase the resolution dynamically and focus only on areas with high belief values.

The overall localisation score is influenced by the sensor measurements quality, the system configuration and a few other factors. In this case, the discretisation of the space may increase the error (see figure 29). The proposed approach introduces a centroid grid-based filtering method based on two layers of grids. The coarse grid is identical to the original approach representing belief values as probabilities of the current position to be within the corresponding grid cell. Another fine layer is used to determine the estimated position which is selected from a set of fine grid cell centers. All components including precomputed convolution masks are adjusted to include all possible combinations of source and target positions defined by a single step.

c: RESULTS ANALYSIS

The overall performance suffers from incorrect initial position based on GNSS measurements. The building structure with narrow corridors and 90° turns supports the Bayesian filtering in reducing the uncertainty introduced by noisy measurements and unknown step length. However, outdoor environment and large open areas are more challenging and demanding on the parameter configuration. In this competition, the first 10–15 checkpoints were difficult to estimate with less opportunities to utilise the building structure to reduce the error. Moreover, the error was not trivial to distinguish from the path with unknown ground truth positions. Another sensitive situation resulting in error increase was on a balcony which was not clearly recognizable from the floor plans. Nevertheless, floor transitions and positioning when walking along the corridors were reliable.

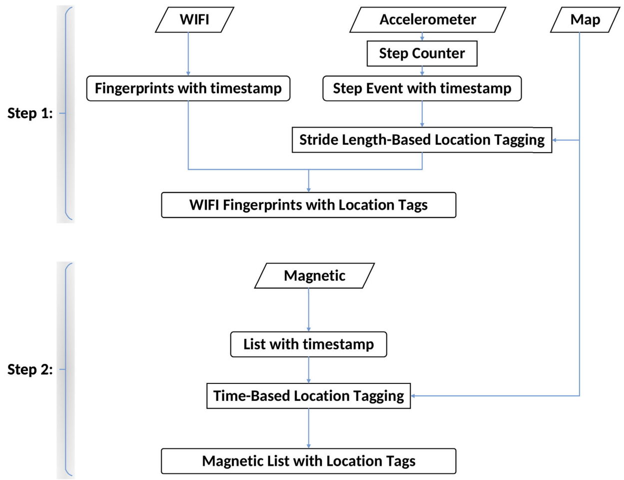

FIGURE 30. Flowchart of the two-stage positioning method, in which step-1 generates a Wi-Fi fingerprint table and step-2 produces a magnetic field strength table.

8) YAI TEAM

The data processing flow chart of the proposed two-stage positioning method is shown in figure 30, which is extended from our previous work [9, YAI team, C-8, Sec. IV]. Our fingerprinting method first leverages the three-axis accelerometer to build a trusted known points associated with APP time. Next, we use the sensed Wi-Fi signal data to generate a Wi-Fi fingerprint table, which contained location information, i.e., longitude and latitude. Then, we compare both the Euclidean distance and the similarity between the sensed N-tuple RSS values and the Wi-Fi fingerprint table data to estimate the coarse positioning results, which will be served as the input information for the fine positioning method. Finally, we fuse the coarse positioning results $\mathbf{P}_W$ with the fine positioning results $\mathbf{P}_M$ to infer the finally positioning results.

a: STEP 1

The main purpose of Step 1 is to produce the Wi-Fi fingerprints, which is used for coarse positioning. In this step, we used the step-detection-assisted fingerprinting method [9, YAI team, C-8, Sec. IV] to make a fingerprinting table. Then, we compare both the Euclidean distance and the similarity of the Wi-Fi receiving behavior metric to obtain coarse positioning results $\mathbf{P}_W$.

b: STEP 2

The training dataset gives the location (longitude and latitude) of some known points, i.e., *POSI*, but these POSI points are

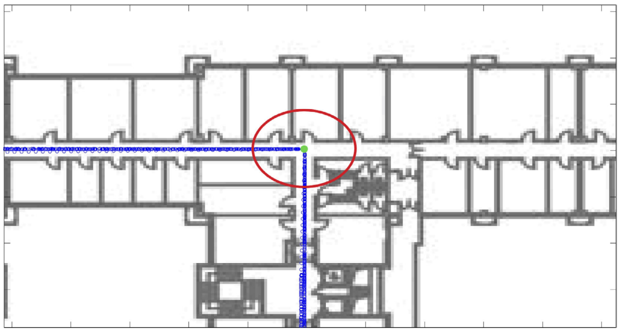

FIGURE 31. Schematic view of cooperation between Wi-Fi positioning results and magnetic positioning results.

sparse in the space domain. First, we artificially construct a magnetic field strength table by linear interpolation method such that each sensed magnetic data has its corresponding location tags. Second, we exploit the coarse positioning results $\mathbf{P}_W$ as the initial point and choose the data record in the magnetic fingerprints which are within the circle with radius of 1 m. The schematic view of cooperation between Wi Fi positioning results and magnetic positioning results is illustrated in figure 31. Note that we exclude all particles outside the circle, where the blue dots are all particles that has a sensed magnetic field value.

The point where similar Wi-Fi similar value obtained in the second step is the center of the circle. We extract the position point with the effective magnetic field value within radius of 1 m. Note that the particles are chosen from the magnetic fingerprinting table. First, N_p particles are randomly selected within the circle, and their weights associated with each particle are calculated individually as follows:

$$w(i) = \frac{1}{\sqrt{2\pi R}} \exp^{\left\{-\frac{Z_i^2}{2R}\right\}} \quad (9)$$

where $w(i)$ represents the weight value assigned to the i-th particle, Z_i denotes the magnetic field value difference between the magnetic field value of the testing point, whose location is to be estimated, and the magnetic field value of the particle $\mathbf{p}_i$, and R represents a pre-defined measurement noise parameter. Note that we have chosen $R = 10^{-11}$ in the simulation. After normalizing the weight values and resampling particles, we are able to obtain a new particle group $\mathbf{p}(i)$ and calculate the center position of this group as follows:

$$\mathbf{P}_M = \frac{1}{N_p} \sum_{i=1}^{N_p} \mathbf{p}(i) \quad (10)$$

It should be noticed that because of the magnetic field strength value is not unique, the coarse positioning results $\mathbf{P}_W$ are considered to be fused with the fine positioning result as follows:

$$\mathbf{P}_F = \lambda \mathbf{P}_W + (1-\lambda)\mathbf{P}_M \quad (11)$$

where $\mathbf{P}_F$ is the final coordinate of the testing point. We empirically choose $\lambda = 0.3$ in our simulation.

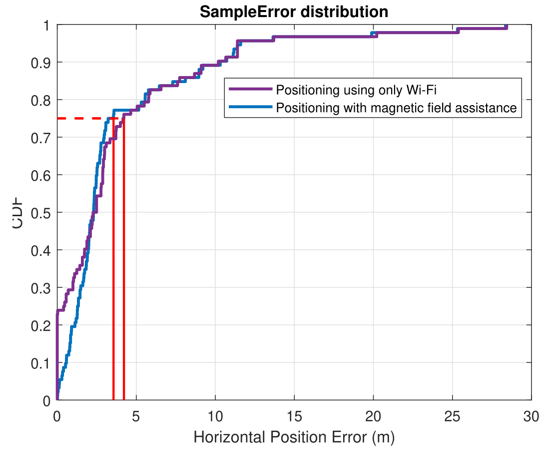

FIGURE 32. The resulting CDF of the positioning errors, in which the purple line indicates the positioning error using only Wi-Fi, and the blue line indicates the expected result after adding the magnetic field.

c: SIMULATION RESULTS

We use the competition files to evaluate the performance of the proposed positioning algorithm. Using the validation data, we obtain the resulting CDF curves of the errors in positioning are shown in figuer 32. It can be seen that when locating using only Wi-Fi, the third quartile of the positioning errors is 4.2 m. After adding magnetic field positioning, the value drops to 3.6 m, thus significantly reducing positioning errors.

VII. TRACK 4 - FOOT-MOUNTED IMU-BASED (OFF-SITE)

A. TRACK DESCRIPTION

The fourth Track was dedicated to foot-mounted inertial and GNSS navigation in an *off-site* context. Data were collected with the PERSY (PEdestrian Reference SYstem, see table 5) sensor developed by the GEOLOC team at University Gustave Eiffel. Track chairs collected the data by walking through the competition area over a 1.1 km path spanning three different floors, using a lift and including some outdoor parts, as shown in figure 33. Track 4 followed the same data collection strategies of the off-site competitions organised in previous years [9]. In contrast with all the other Tracks, where competitors were provided with a detailed map beforehand and could make use of that information, competitors in Track 4 could not use any map information.

Two data sets were given to competitors. Dataset n°1 was taken on a single static location for several hours, and was meant to be used for sensor calibration, by enabling competitors to compute noise and measurement bias of inertial sensors (Allan variance). Dataset n°2 was the data recorded on CNR Area following 6 different steps, as shown in table 4 and in figure 34.

The competitors' objective was to re-build the trajectory realised by the Track chairs. The evaluation was done by comparing 2D position and floor level estimated by each team to the coordinates of 68 reference points (key points). To do so, a table containing timestamps of expected key points

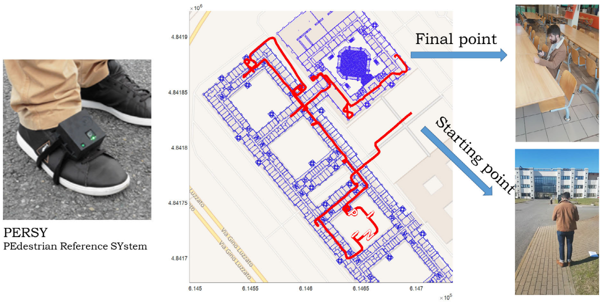

FIGURE 33. PERSY and description of Track 4 over CNR facilities.

TABLE 4. Different steps composing Dataset n°2 over CNR facilities.

Step	Duration	Description
Step1	10s	hand held static phase
Step2	60s	magnetometer calibration
Step3	10s	hand held static phase
Step4	2min	PERSY setup on the foot
Step5	60s	static phase with PERSY on the foot
Step6	25min	evaluation Track including key points from 1 to 68

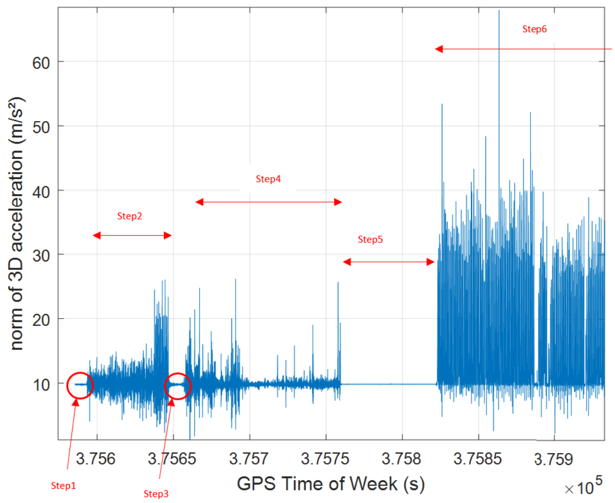

FIGURE 34. Different steps composing Dataset n°2 over CNR facilities.

TABLE 5. Information about embedded sensors inside PERSY.

Sensor	Model & Manufacturer	Sampling Freq. (Hz)
Accelerometer	STIM300 - Sensonor	160
Gyroscope	STIM300 - Sensonor	160
Magnetometer	HMC5983 - Honeywell	160
GNSS	NEO-M8T - Ublox	5

was shared, and competitors had to provide the corresponding coordinates.

Data Set and supplementary materials –e.g. datasheet of sensors embedded in PERSY– were provided to competitors of Track 4. These contents and the ground truth location for evaluation are now available for further benchmarking in [41]. This package complements the ones from the previous editions [42].

B. INDOOR POSITIONING SOLUTIONS PROVIDED BY COMPETITORS

1) KIU SNU TEAM

A disadvantage of the zero velocity update (ZUPT)-based pedestrian dead reckoning (PDR) is that a large positioning error occurs if the stance phase of the foot mounted with the inertial measurement unit (IMU) is erroneously detected. To solve this problem, we propose an accurate zero-velocity detection method. We then use this to implement an accurate ZUPT-based foot-mounted inertial navigation system (INS).

a: ACCURATE ZERO-VELOCITY DETECTION

When the IMU is mounted on the foot, the PDR can be developed in two directions, respectively. One is positioning by step detection, stride estimation, and azimuth calculation [43]. The other is positioning by the INS algorithm and the error correction via ZUPT [44]. The beginning of the PDR in the early 2000s started with the first method. However, as the performance of MEMS-type IMU is improved recently, the second method is widely used. Instead of ZUPT, a method of velocity correction by calculating foot velocity has been studied recently [45]. In this paper, PDR is developed based on the second method, and this method is called ZUPT-based PDR. The advantage of the ZUPT-based PDR is that it can estimate the position of the foot regardless of the various walking patterns of the foot. However, if the stance phase with zero-velocity is not accurately detected for ZUPT, a large positioning error may occur. Therefore, in this paper, we propose a method to detect the accurate zero-velocity through signal processing of IMU output in order to develop stable ZUPT-based PDR. Figure 35 illustrates the key to accurate zero-velocity detection.

Figure 35 shows that the signal processed data (Sensor-T) is greatly simplified during the stance phase by buffering the sensor signal and calculating the standard deviation of the buffer. Through this signal, it is possible to accurately detect the section of zero-velocity. Figure 36 shows an example of the zero-velocity detection during the stance phases using real data provided in Track 4.

b: ZUPT-BASED FOOT-MOUNTED INS

Using the 3-axis accelerometer and gyro output of the IMU, the navigation information of the foot attaching the IMU can be calculated based on the INS algorithm. However, the errors of navigation information gradually increase with time due to the errors of the inertial sensors such as bias repeatability, random walk, etc. Therefore, it is common to construct an integrated navigation system that corrects the INS errors by using an appropriate non-inertial sensors.

Additional sensor information provided by Track 4 is GNSS-based position information and 3-axis magnetometer information. The azimuth information calculated using the magnetometer is not stable due to the influence of the surrounding magnetic field. Therefore, in this paper, we use the initial GNSS information to determine the initial walking

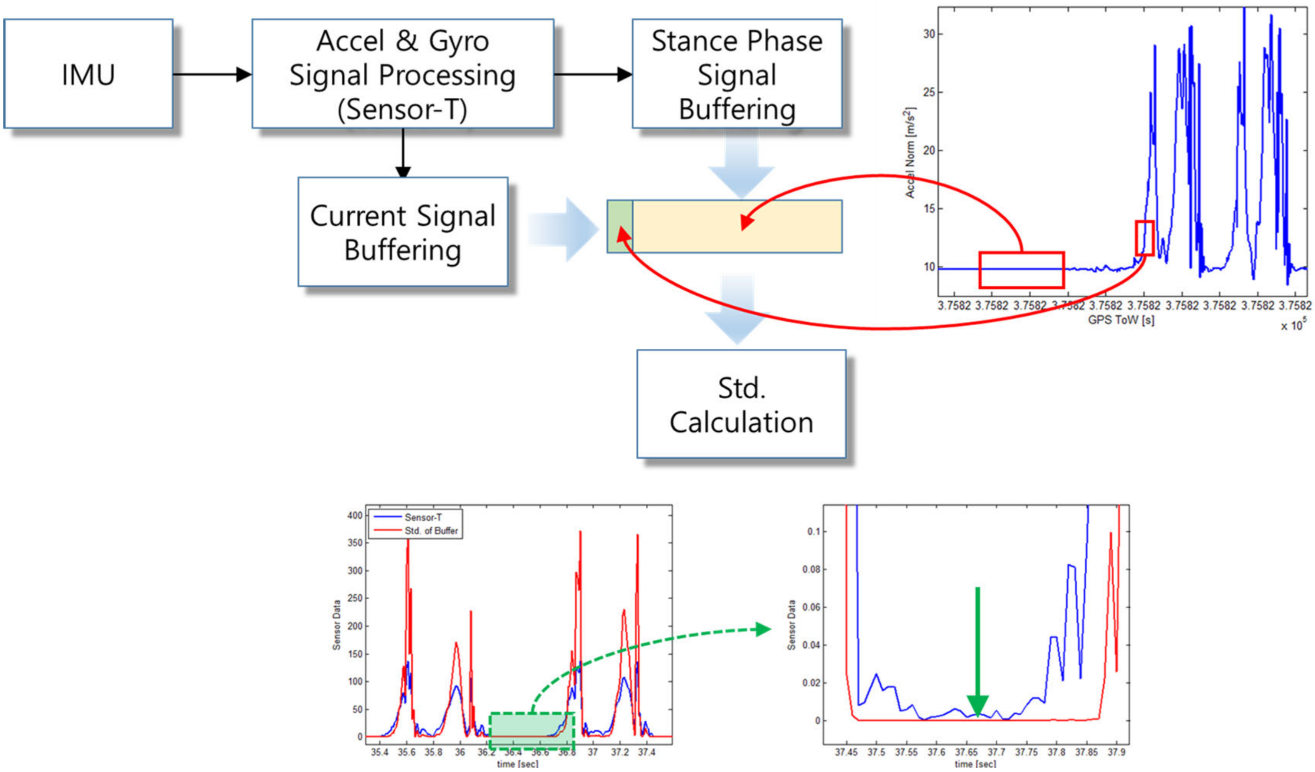

FIGURE 35. Main processing for zero-velocity detection.

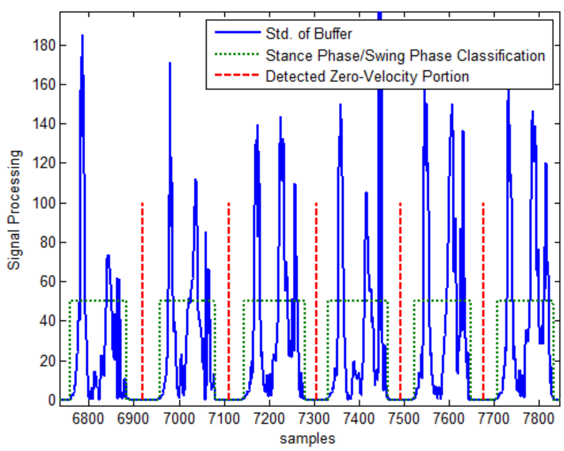

FIGURE 36. An example of the zero-velocity detection.

direction and correct the INS errors through the ZUPT at the accurate zero-velocity point that can be detected based on the method presented in the previous section. Figure 37 illustrates the functional structure of the ZUPT-based foot-mounted INS. ZUPT is designed based on an extended Kalman filter, and state variables are set by position error, velocity error, attitude error excluding azimuth, and accelerometer bias. The gyro bias was excluded because it was calibrated through the average of the gyro output during the initial alignment process, and the azimuth was excluded because it is not observable in ZUPT. When the altitude change occurs through the

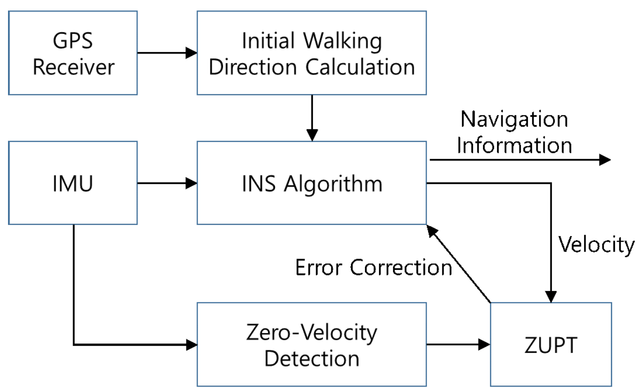

FIGURE 37. Functional structure of the ZUPT-based foot mounted INS.

stair walking, the floor information is calculated by analyzing the characteristics of the altitude information.

2) TEAM KIT

The KIT team used a tightly-coupled INS/GNSS sensor data fusion approach. Zero-Velocity-Updates (ZUPTs) are generated in the detected midstance phases of the foot by a finite state machine based gait phase classifier [46], [47]. In contrast, horizontal ZUPTs and delta ZUPTs are applied during stance phases using an lift. Absolute velocity measurements are generated during stance phases on an escalator [48]. If GNSS pseudo-range and Doppler measurements are available, the kind of aiding depends on the current classified motion state. To enable accurate position estimation in urban scenarios an integrity check of the received GNSS data is essential [49]. Based on the described measurements, corrections of the navigation solution and the bias values of the inertial sensors are calculated by an error-state Kalman filter.

a: GAIT PHASE CLASSIFIER

The used finite state machine based motion classifier method is founded on bio-mechanical knowledge and medical research findings of the human gait. Because the foot module is just mounted on one foot, it is appropriate to model four basic motion states for forward motion described in detail in [46]. The transitions and states representing backwards motion and the detection of walking and running are explained in [47].

b: LIFT AND ESCALATOR DETECTOR

The approach is able to detect and separate lift from escalator movements [48]. In addition, the lift and escalator rides are subdivided in different sub-states like acceleration phase, constant velocity phase and braking phase. The lift and escalator detector is realised with two separate finite state machines; one for the recognition of lifts and the second for the detection of escalators. The finite state machines have different states and transitions to switch between the states.

c: GNSS AUGMENTATION

The precise relative positioning INS is fused with GNSS pseudo-range and Doppler measurements for absolute position and heading estimation. Unique is the decision depending on the classified motion state if Doppler measurements improve the accuracy of the navigation solution. In addition, the integrity of the GNSS signals are checked. A good knowledge of the precise relative positioning inertial system is used to detect and exclude GNSS measurements with high multipath errors. This is essential for robust pedestrian localisation in dense urban environments with outdoor-indoor transitions.

3) AOE TEAM

The pedestrian foot-mounted PDR system proposed by AOE team is shown in figure 38.

In the above framework, five constraint algorithms are included in the middle modules: Stance & Still Phase Detection, the HDE, the HUPT, the ZUPT, and the Earth Magnetic Yaw. Meanwhile, the Stance and Still Phase Detection includes two components: the GLRT detector algorithm used under the condition of the slow and normal pedestrian gait speed, and the HMM detector algorithm used under the condition of the dynamic and fast pedestrian gait speed. After that, using the improved HDE and HUPT method to estimate current position errors, ZUPT is used to estimate the velocity error, while Earth Magnetic Yaw based on QSF method is used to estimate the heading error.

a: THE MULTI-CONSTRAINT ALGORITHMS

A gait or a walk cycle consists of two phases: the swing and stance phase. In the swing phase, the foot is not in contact

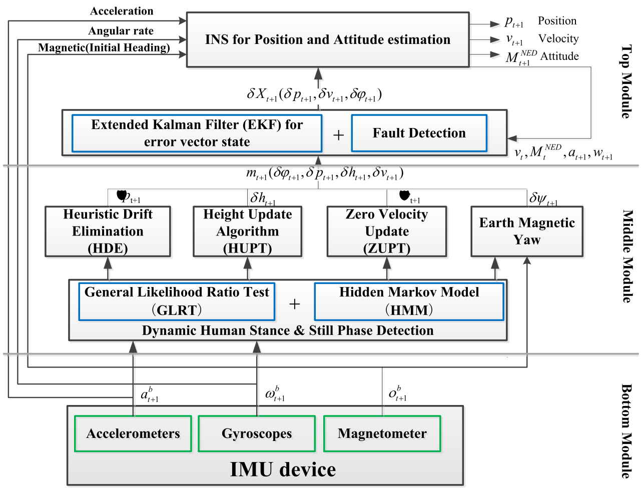

FIGURE 38. **The scheme of foot-mounted PDR system based on multi-constraint algorithms.**

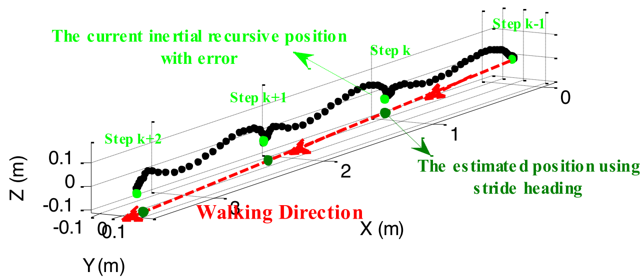

FIGURE 39. **Revise the current step's inertial recursive position with the position calculated from the stride heading.**

with the ground. In contrast, the foot contacts the ground in the stance phase. GLRT algorithm has obvious advantages for zero speed detection of stable pedestrian gait velocity, while HMM algorithm has a good effect for zero speed detection of dynamic and fast pedestrian gait speed. Thus, the two methods are combined to achieve the dynamic human stance and still phase detection [50].

When the Stance and Still Phase Detection detects the stance and swing phases of human foot gait from IMU's data, ZUPT method is used to constraint the velocity divergence [51].

HDE algorithm is a very useful method to constraint the system's heading drift, if the indoor reference heading can be known in advance. In our method, we used the initial heading to calculate several possible reference directions of pedestrian walking [52]. Then, unlike the existing HDE method, which mainly corrects inertia recursive heading, we use the closest reference direction to calculate the estimate position at the current footstep, then uses the position error between the estimate position and the inertia recursive position to restrain the position divergence. The procedure is shown in figure 39.

Height divergence is a major problem in INS-based foot-mounted PDR system in multi-story positioning. If pedestrian walking on a plane, the slope of the current stride is approximately zero degree, if that, keep the height always unchanged.

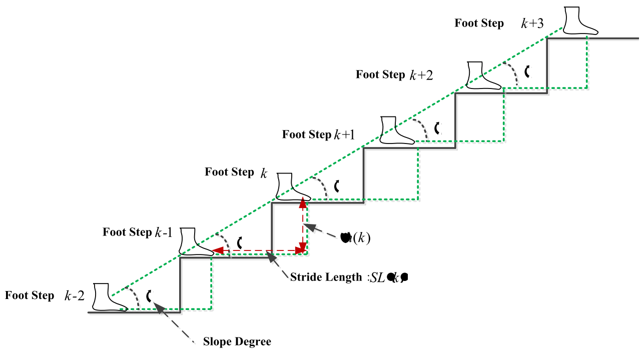

FIGURE 40. **The slope of adjacent footsteps when walking on staircase.**

While walking on a staircase, as shown in figure 40, we proposed to use the actual slope of the stairs (usually 20–45°) to calculate the height change of the current stride, which can be used to constrain the height divergence of the current stride [52]. If pedestrian is on an lift or escalator, it mainly can be effectively determined by analyzing the characteristics of acceleration, especially the acceleration in the vertical direction.

The magnetic field is very useful to estimate the heading of the system, but the magnetic disturbance has a severe effect on the estimation. In our method, an improved QSF method combined with a compass filter is used to estimate the heading in the perturbed magnetic field [53]. In addition, in areas where pedestrians repeatedly walk, we use a series of magnetic sequence information for pedestrian trajectory matching to improve the effect of heading constraint.

VIII. DISCUSSION AND LESSONS LEARNT

A. DISCUSSION

Most teams competing in the on-site challenges performed a comprehensive survey of the competition area the day before the competition. As in previous editions, paths were not disclosed until the start of the trials, which forced competitors to survey a rather large area in a short time.

In **Track 1** we see three teams scoring under 15 m, with the best one at 3.8 m. The competition area was a challenging scenario for smartphone-based systems mainly due to a mix of corridors where PDR techniques can give their best, and wide and open areas where Wi-Fi based evaluation can represent the best option to detect the device's position. Only robust systems able to effectively fuse multiple sources of information could show good performance. The winner and the runner-up of Track 1 have shown very notable results. In particular, the winner team, SNU-NESL, reached a remarkable score of 3.8 m and their accuracy exhibited an impressive 95th percentile of 7.3 m. It is worth noting how the 95th percentile can be considered a metric for systems which approach the market and, generally, research-grade systems show bigger errors than the results reached by the 2019 winner. As described in section IV, competitors have developed algorithms which consider all the available sensors (inertial, magnetic, barometric, Wi-Fi). The differences in terms of final score are related mainly to the different weights that competitors gave to the real-time sensor readings, the off-line fingerprint database and the algorithm for evaluating the user orientation and step length.

In **Track 2** we again see three scores under 15 m, with the best one at 3.6 m. As discussed in section V, the competition area was quite challenging for vision-based systems due to several aspects. The experience of the vision-based competitions in 2018 and 2019 highlights that survey time constraints were critical in achieving good results. The winner team, HANA Micron, has shown the best accuracy among on-site competition teams. HANA Micron adopted object detection as a way of error correction, which demonstrated to be quite a smart approach in terms of saving survey time and processing time. The other three teams suffered from having to surveying and mapping the whole competition area within only 9–10 hours, which was the main reason for the incomplete results of the Kyushu University team. Baseline technologies were similar across teams; the differences in scores were mainly due to proficiency in dealing with exceptions.

In **Track 3** 12 teams scored under 7 m, with the best one at 2.3 m. In contrast with the on-site Track 1, which is also based on smartphone only, in Track 3, which is off-site, the reference data is provided to competitors in advance. Competitors had some weeks to process the pre-collected data and, therefore, the positioning results are better. All the methods providing an accuracy score below 3 m applied sensor fusion to provide positioning, involving a Kalman filter most of the time. Deep PDR and Fastgraph [38] techniques, context and activity information seem to be promising at different stages. It is interesting to note that none of the competitors ensembled different approaches to minimise the positioning error. However, ensembling the estimations provided by the winner and the runner-up (sample data provided in [29]) would have ended in the best overall score for Track 3.

In **Track 4** three teams scored under 4 m, with the best one at 1.6 m. This year, similarly to the previous edition, maps were not allowed to help computation of the final position. Competitors had to analyze motion (acceleration, rate of turn) very carefully in order to correctly detect the positions of the reference points. Common ZUPT methods coupled to strapdown integration have been used by competitors in order to rebuild trajectory by a double integration of accelerometer. Best teams had to use additional sensors like magnetometer and GNSS signal to initiate and keep a proper heading, which is a crucial point in the dead reckoning process. Among reasons for score difference are the perfect estimation of floor levels and the use of up-to-date techniques of ZUPT (KIU SNU), GNSS doppler and pseudoranges (KIT) and QSF for magnetometer (AOE).

B. LESSONS LEARNED BY COMPETITORS

This section is based on feedback from competitors, edited as a summary of observations. In general, competitors appreciated participating in the competition. The most cited reasons were the opportunity to meet other teams who were working on very similar topics, the chance to discuss their ideas and get inspiration and also the possibility of creating collaboration liaisons. They appreciated the well-staffed organisation of the competition and the attention to details and provided some suggestions for improvement.

Here is a summary of the main lessons learned in the competitors' view.

- Competitors had the opportunity of integrating and testing their indoor positioning systems with limited time available in a realistic setting on a scale much larger than what is usual in a laboratory. These challenges, together with having to deal with a path with standby delays, providing real-time estimates and using commercial off-the-shelf hardware allowed to pinpoint weaknesses in the systems.
- Some competitors argued that the competition revealed that fingerprinting, especially Wi-Fi fingerprinting, is not a viable solution to future indoor localisation technology. With the advent of 5G, the cellular signal holds much promise for more precise indoor positioning.
- Track 2 competitors realised that the tracking camera is very sensitive to changes in light strength. Few events where major tracking errors were recorded while moving from indoors to outdoors on a sunny day had a huge impact on the final score.
- Some teams successfully profited from deep learning techniques and see a prospect of more widespread adoption in indoor positioning in the near future.
- There is some controversy about how an ideal evaluation should start. Currently, the initial position is provided to competitors at the beginning of the competition. Developers of pure PDR-based solutions feel that initial heading must be provided too, whereas competitors dealing with multiple sources of data (sensor fusion) stress the necessity of being autonomous to deal with the case when the user suddenly requests location information. Efforts are needed to reduce the importance of getting the initial position and heading from an external source.
- Most competitors share the idea that combining multiple complementary technologies is the future of indoor positioning. Some are considering the inclusion of the light sensor to improve system accuracy.
- Independent evaluation has been an incentive for all. For many competitors, it is a badge to have their indoor positioning solution externally evaluated with a rigorous procedure under realistic and challenging conditions such as having just one day for on-site calibration.

IX. CONCLUSION

The IPIN Competition series is the most important showcase of worldwide indoor localisation technology. Since 2014, it has compared the performance of personal localisation systems in real-time using the rigorous EvAAL framework. Every year, the IPIN competition has published the results obtained by academic and industrial competitors who put their systems to test in challenging environments with realistic procedures on a level field.

Because of the pandemic, 2020 is the first year since the IPIN Competition inception that on-site competition will be withheld, but the off-site Tracks, which were launched in 2015, will be held as usual, and increasing in number from three to five.

Of the 25 teams competing in 2019 in Tracks 1–4, 19 accepted to contribute to this paper and concisely described their working system for on-site Tracks 1 and 2 or their algorithm for off-site Tracks 3 and 4. This collection is arguably the best description we can get today of state of the art in personal indoor localisation systems, both at the prototypical and the algorithmic level.

The variety of methods and the lessons learned exposed by the participants in the IPIN 2019 Competition show how much this field is bubbling with activity, and why we have not yet got a universal indoor localisation system that works in a general and cheap way as GNSS works outdoors. Indeed, the main problem is that while outdoors we can almost always see the sky (from a radio wave perspective), we don't have any instance of a single source of information indoors. Add to this that the accuracy that is needed indoors is generally higher than the one needed outdoors, and that 2D is good enough outdoors, but one needs at least 2.5D indoors. The IPIN competition helps us understand why, after at least ten years of research on personal indoor localisation, only now we are starting to get a glimpse of a generic solution, which is not there yet.

There is at least one more takeaway to the IPIN Competition. It is the striking difference, which could be observed since the first competition and has been consistent since then, between the accuracy performance claimed by essentially all the literature on one hand, and the one we are able to measure on the other hand. This is true both for the on-site and the off-site Tracks. In 2019 we observed a record-breaking third quartile accuracy of 3.8 m and 3.6 m in the on-site Tracks, and 2.3 m and 1.7 m in the off-site Tracks. However, it is not uncommon to read papers claiming sub-meter accuracy. The reason is not bad science or wrong measurement procedures. Rather, the reason is that the vast majority of researchers cannot afford to set up a rigorous external measurement procedure as described by the EvAAL framework and implemented during the IPIN competitions.

The IPIN competitions have played an essential role in the academic and industrial research on indoor localisation and seamless location-based services, which are enablers for an enormous market that will develop in the near future. They are going to play it for the foreseeable future as well.

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AUTHOR CONTRIBUTIONS

The IPIN 2019 Competition was organized and hosted by ISTI in Pisa, an institute of the National Research Council (CNR) of Italy. Francesco Potortì chaired the competition, wrote the abstract, introduction, competition description, and conclusions, and was responsible for the final overall review of the paper.

Track 1 – Smartphone-based challenge (on-site) – Antonino Crivello contributed to the overall organization of the paper. Together with Filippo Palumbo managed the description and paper collection of Track 1. Michele Girolami contributed the description of the measurement app.

Track 2 – Video-based challenge (on-site) – the organizing team was composed of Soyeon Lee and Sangjoon Park, who coauthored this paper. Blagovest Vladimirov also contributed to the competition by supporting the analysis of the scores for Track 2 teams.

Track 3 – Smartphone-based challenge (off-site) – the organizing team was composed of Joaquín Torres-Sospedra and Antonio Ramón Jimenez, who also led the writing of this paper. Antoni Pérez-Navarro, Germán Martín Mendoza-Silva, and Fernando Seco also contributed to this paper by organizing Track 3, collecting contributions, and reviewing the paper.

Track 4 – Foot-mounted PDR (off-site) – Miguel Ortiz managed the section on Track 4.

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- T3 – IOT2US: Bang Wu (corresponding author, e-mail: bang.wu@qmul.ac.uk), Chengqi Ma, Stefan Poslad, David R. Selviah, Wei Wu, and Zixiang Ma
- T3 – AraraDS: Tomás Lungenstrass (corresponding author, e-mail: tomas@ararads.com) and Vicente Cortés
- T3 – UMinho: Adriano Moreira (corresponding author, e-mail: adriano.moreira@algoritmi.uminho.pt), Maria João Nicolau, Cristiano Pendão, Ivo Silva, Filipe Meneses, and António Costa
- T3 – UGent: Jens Trogh and David Plets (corresponding author, e-mail:david.plets@ugent.be)
- T3 – INDORA: Miroslav Opiela (corresponding author, e-mail: miroslav.opiela@upjs.sk)
- T3 – YAI: Ying-Ren Chien (corresponding author, yrchien@niu.edu.tw), Tzu-Yu Chang, Shih-Hau Fang, and Yu Tsao.
- T4 – KIU SNU: Seong Yun Cho (corresponding, e-mail: sycho@kiu.kr), Jae Hong Lee, and Chan Gook Park
- T4 – KIT: Nikolai Kronenwett (corresponding author, e-mail: nikolai.kronenwett@kit.edu) and Silvia Prophet
- T4 – AOE: Wenchao Zhang (corresponding, e-mail: zhangwenchao@aoe.ac.cn), Dongyan Wei (corresponding, e-mail: weidy@aircas.ac.cn), and Hong Yuan

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FRANCESCO POTORTÌ (Member, IEEE) is currently a Senior Researcher with ISTI-CNR, Pisa, Italy, where he has been working since 1989 in the field of satellite and terrestrial communications. He has organized the 2011–2013 EvAAL competitions, defined the EvAAL framework, organized the IPIN competitions from 2014 to 2017, and chaired the tenth edition of the IPIN conference and the sixth edition of the IPIN Competition in 2019. His current research interests include RSS-based indoor localization, interoperability, and evaluation of indoor localization systems. He has coauthored more than 80 peer-reviewed scientific articles. He is also a member of the IPIN steering board.

SANGJOON PARK received the B.S. and M.S. degrees in electronics engineering from Kyung-Pook National University, in 1988 and 1990, respectively, and the Ph.D. degree in computer science from North Carolina State University, in 2006. He worked as a Senior Researcher with the Agency for Defense Development (ADD) from 1990 to 2001. Since 2006, he has been the Director of the positioning and navigation technology with the Electronics and Telecommunications Research Institute (ETRI), South Korea. His current research interests include positioning, wireless sensor networks, next-generation embedded sensor networks, multisensor data fusion, and target tracking.

ANTONINO CRIVELLO (Member, IEEE) received the Ph.D. degree in information engineering and science from the University of Siena, Italy, in 2018. He is currently a Researcher with the Information Science and Technology Institute, Consiglio Nazionale delle Ricerche (ISTI-CNR), Pisa, Italy. His research interests include indoor positioning and ambient-assisted living.

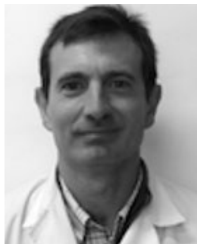
FILIPPO PALUMBO (Member, IEEE) received the M.Sc. degree (Hons.) in computer science engineering from the Polytechnic University of Bari, Italy, in 2010, and the Ph.D. degree in computer science from the University of Pisa, Italy, in 2016. He is currently with ISTI-CNR. His research interests include the application of AI to wireless sensor networks for intelligent system design and software development in distributed systems. He has participated in several EU- and national-funded research actions in the areas of ambient intelligence.

MICHELE GIROLAMI received the M.Sc. and Ph.D. degrees in computer science from the University of Pisa, in 2007 and 2015, respectively. He is currently a Research Staff with the Wireless Network Laboratory, ISTI-CNR. He participates in several EU projects as well as national projects. His research interests include social interaction analysis, mobile social sensing, and crowdsensing techniques in urban contexts.

PAOLO BARSOCCHI received the M.Sc. and Ph.D. degrees in information engineering from the University of Pisa, Italy, in 2003 and 2007, respectively. He is currently working as a Researcher with ISTI-CNR. He has coauthored more than 100 articles published in international journals and conference proceedings. He has been a member of numerous program committees, the Program Chair of several conferences, and he is a part of the editorial board of international journals. His research interests include wireless mobile systems and architectures, cyber-physical systems, indoor localization, and wireless sensor networks.

SOYEON LEE received the B.S. degree in statistics from Ewha Womens' University, in 1992, the M.S. degree in statistics of computation from Seoul National University, in 1994, and the Ph.D. degree in computer and information science from Korea University, in 2015. Since 1994, she has been a Principal Researcher with the Electronics and Telecommunications Research Institute (ETRI), South Korea. Since 2013, her research topic is pedestrian dead reckoning focusing on foot-mounted and handheld devices. Since 2016, she has also been chairing one of the competition tracks in IPIN, Indoor Positioning and Indoor Navigation. She was an Associate Rapporteur of Question 27/WP2 of ITU-T SG16. Also, from 2017 to 2018, she has served as a Standardization Director for the Korean Society of Automotive Engineers. Her current research interests include indoor positioning using pedestrian dead reckoning and Bayesian filtering, human interaction in AR/VR, and their military training applications.

JOAQUÍN TORRES-SOSPEDRA was born in Castelló, Spain, in 1979. He received the Ph.D. degree in ensembles of neural networks and machine learning from Universitat Jaume I, in 2011. In April 2013, he joined the Institute of New Imaging Technologies (INIT, Universitat Jaume I), where he led Indoor Positioning projects. Since January 2020, he has been the Scientific Coordinator of UBIK Geospatial Solutions and still collaborates with INIT, as well as other international research institutions. He has authored more than 120 articles in journals and conferences. He has supervised five master and two Ph.D. students. He is also supervising six Ph.D. students. His current research interests include indoor positioning solutions based on Wi-Fi and BLE, machine learning, and evaluation. He is also the Chair of the IPIN International Standards Committee and IPIN Smartphone-Based Off-Site Competition.



ANTONIO RAMÓN JIMÉNEZ RUIZ was born in Santander, Spain, in 1968. He received the degree in physics and computer science and the Ph.D. degree in physics from the Universidad Complutense de Madrid, Madrid, Spain, in 1991 and 1998, respectively. Since 1993, he has been with the Center de Automation y Robotics, Spanish Council for Scientific Research, Madrid, where he holds a research position. He has authored more than 100 articles in journals and conference proceedings. His current research interests include local positioning solutions for indoor/ GPS-denied localization and navigation of persons and robots, signal processing, Bayesian estimation, and inertial-ultrasonic-RFID sensor fusion. He is a reviewer for many international journals and projects in the field.

ANTONI PÉREZ-NAVARRO (Member, IEEE) received the bachelor's degree in physics from the Universitat Autònoma de Barcelona(UAB), in 1995, and the Ph.D. degree in physics from UAB. He is currently the Director of the Technological Observatory, Department of EIMT, the Director of the technical collection of books of editorial Ediuoc, the Deputy Director of Research with the eLearn Center, Universitat Oberta de Catalunya (UOC), and a Lecturer with the Department of Computer Science, Multimedia and Telecommunication (EIMT Department). He is also working with the Escola Universitària Salesiana de Sarrià (EUSS), where he provides classes in Industrial Engineering grades. His research interests include indoor positioning and the prevention of diseases via smartphones. He has published several articles in international journals on all these topics and acts as a reviewer of several journals. He is a part of the Technical Program Committee of IPIN and is one of the organizers of the symposium "Challenges of Fingerprinting in Indoor Positioning and Navigation" that was held in Barcelona in 2015.

GERMÁN MARTÍN MENDOZA-SILVA received the bachelor's degree in computer science from the University of Oriente, Cuba, in 2005, and the M.Sc. degree in geospatial technologies from WWU, Germany, UNL, Portugal, and UJI, Spain, in 2015. He is currently pursuing the Ph.D. degree with the Institute of New Imaging Technologies, UJI, with a focus on WLAN-based indoor positioning, indoor navigation, machine learning, and GIS applications.

FERNANDO SECO was born in Madrid, Spain, in 1972. He received the degree in physics from the Universidad Complutense of Madrid, Madrid, in 1996, and the Ph.D. degree in physics from the Universidad Nacional de Educación a Distancia, Madrid, in 2002, with a dissertation about the magnetostrictive generation of ultrasonic waves applied to a linear position sensor. Since 1997, he has been with the Center for Automation and Robotics, Spanish Council for Scientific Research, Arganda del Rey, Madrid, where he holds a research position. His current research interests include the design and development of indoor local positioning systems, especially those based on ultrasonic and radio-frequency technologies in signal processing for CDMA-based localization systems and in Bayesian estimation.

MIGUEL ORTIZ received the M.Sc. degree in mechanics, automation and engineering from the Ecole Nationale Supérieure d'Arts et Métier, in 2001. He joined the lab after spending six years in a company, where he managed systems architecture for automotive applications. He has now 12 years of experience in the GNSS domain (Research Engineer). Since 2019, he has been the Head Deputy of the GEOLOC Laboratory, Gustave Eiffel University. He is currently a Research Engineer with the GEOLOC Laboratory, University Gustave Eiffel (ex-IFSTTAR). He is also an Expert in embedded electronic systems. His research interests include software and hardware developments for both intelligent transport systems (ITS) and the pedestrian navigation research field. Since 2017, he has been the Convenor of CEN/CENELEC TC5-WG1 named "Navigation and positioning receivers for road applications."

JOHAN PERUL received the engineering degree in topography from the Ecole Superieure des Geometres et Topographes, Le Mans, France. After working for a year in Parallèle 45 Company as a 3D Engineer, he began his Ph.D. "Autonomous localization by learning displacement dynamics in multimodal transport" in 2017 at the GEOLOC Laboratory, University Gustave Eiffel (ex-IFSTTAR), Nantes, France.

VALERIE RENAUDIN (Member, IEEE) received the M.Sc. degree in geomatics engineering from ESGT, in 1999, and the Ph.D. degree in computer, communication, and information sciences from EPFL, in 2009. She was a Technical Director of Swissat Company, Samstagern, Switzerland, developing real-time geopositioning solutions based on a permanent global navigation satellite system (GNSS) network, and a Senior Research Associate with the PLAN Group, University of Calgary, Canada. She is currently leading the Geopositioning Laboratory (GEOLOC), University Gustave Eiffel (ex-IFSTTAR), France, where she built a team specializing in positioning and navigation for travelers in multimodal transport. She is also a Research Director (Full Professor) of the University Gustave Eiffel (ex-IFSTTAR). Her research interests include outdoor/indoor navigation using GNSS, and inertial and magnetic data, particularly for pedestrians to improve sustainable personal mobility. She has been a member of the IEEE society since 2013 and the steering committee of the international conference on "Indoor Positioning and Indoor Navigation." She was a recipient of the European Marie Curie Career Integration Grant for her project smartWALK.

HYUNWOONG KANG was born in Seoul, South Korea, in 1994. He received the B.S. degree in mechanical engineering from Seoul National University, Seoul, South Korea, in 2019, where he is currently pursuing the integrated M.S. and Ph.D. degree with the Department of Mechanical and Aerospace Engineering.

SOYOUNG PARK (Member, IEEE) received the B.S. degree from the School of Mechanical and Electrical Control Engineering, Handong Global University, in 2013. She is currently pursuing the Ph.D. degree with the School of Mechanical and Aerospace Engineering, Seoul National University, Seoul, South Korea. Her research interests include pedestrian dead reckoning, smartphone-based indoor navigation, context awareness, and AHRS.

JAE HONG LEE (Graduate Student Member, IEEE) received the B.S. degree from the School of Mechanical and Electrical Control Engineering, Handong Global University, in 2017, and the M.S. degree from the Department of Mechanical and Aerospace Engineering, Seoul National University, Seoul, South Korea, in 2019, where he is currently pursuing the Ph.D. degree with the Department of Mechanical and Aerospace Engineering. His research interests include pedestrian dead reckoning and inertial navigation systems.

CHAN GOOK PARK (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in control and instrumentation engineering from Seoul National University, Seoul, South Korea, in 1985, 1987, and 1993, respectively. He worked with Prof. J. L. Speyer on peak seeking control for formation flight at the University of California, Los Angeles (UCLA) as a Postdoctoral Fellow in 1998. From 1994 to 2003, he was an Associate Professor with Kwangwoon University, Seoul. In 2003, he joined the School of Mechanical and Aerospace Engineering, Seoul National University, as a Faculty Member, where he is currently a Professor. From 2009 to 2010, he was a Visiting Scholar with the Department of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA, USA. His current research interests include advanced filtering techniques, inertial navigation systems (INSs), GPS/INS integration, MEMS-based pedestrian dead reckoning, and FDIR techniques for satellite systems. He has served as the Chair for the IEEE AES Korea Chapter until 2009.

JISU HA received the B.Eng. degree in computer science and information engineering and the M.Eng. degree in computer science from The Catholic University of Korea, in 2014 and 2016, respectively. From 2016 to 2019, he was a Junior Research Engineer with HANA MICRON, as a Creative Thinking Group. His current research interests include machine learning, indoor positioning systems, and GIS on mobile services.

JAESEUNG HAN received the B.S. and M.S. degrees in robotics from Kwangwoon University, Seoul, South Korea, in 2015 and 2017, respectively. He is currently a Researcher with HANA MICRON, South Korea. His current research interests include image processing, robot design, and indoor positioning.

CHANGJUN PARK received the B.S. degree in computer education from Silla University, South Korea, in 2015, and the M.S. degree in electronics and computer engineering from Pusan National University, South Korea, in 2017. He is currently a Researcher with HANA MICRON, South Korea. His current research interests include machine learning, image processing, the IoT, and cloud computing.

KEUNHYE KIM received the B.S. degree in computer science from Sungshin Women's University, South Korea, in 2015. She is currently a Researcher with HANA MICRON, South Korea. Her current research interests include GIS systems, the IoT, and cloud computing.

YONGHYUN LEE was born in Seoul, South Korea, in 1974. He received the B.S. degree in computer engineering from Soonchunhyang University, South Korea, in 1999. He developed H/W drivers for eBook devices from 2000 to 2002. From 2002 to 2011, he was a Researcher with the Communications Research Institute, Motorola Korea, Inc. He is currently a Researcher with HANA MICRON, as a Development Team Leader. His current research interests include indoor positioning systems and GIS on mobile services.

SEUNGHUN GYE received the B.Eng. degree in computer engineering from Gachon University, South Korea, in 2013, respectively. He developed Android mobile applications from 2013 to 2016. He is currently a Researcher with HANA MICRON, South Korea. His current research interests include indoor positioning systems and GIS on mobile services.

KEUMRYEOL LEE was born in Mokpo, South Korea, in 1980. He received the M.S. and Ph.D. degrees in human–computer interaction from Hanyang University, in 2010. From 2010 to 2014, he was a Principal Researcher with the Korea Telecom Group. He is currently a Digital Transformation Group Director with HANA MICRON, South Korea. His current research interests include artificial intelligence, machine learning, open platform, business intelligence, the IoT, and mixed reality.

EUNJEE KIM received the B.Sc. degree with a double major in electronics engineering and business administration from Myongji University, South Korea, in 2013. She is currently working with the Digital Transformation Group for HANA Micron as a Market Strategist. She is interested in digital transformation and industry 4.0 related to indoor positioning systems.

JEONG-SIK CHOI received the B.S. degree in electrical engineering from the Pohang University of Science and Technology (POSTECH), Pohang, South Korea, in 2010, and the M.S. and Ph.D. degrees in electrical engineering from Seoul National University, Seoul, South Korea, in 2012 and 2016, respectively. From 2016 to 2017, he was a Senior Researcher with the Institute of New Media and Communications, Seoul. Since 2017, he has been with Intel Labs, Santa Clara, CA, USA. His research interests include wireless propagation channel measurement/modeling, sensor fusion and positioning algorithms, and application of machine learning techniques to communication systems.

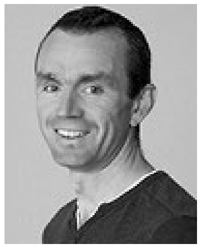
YANG-SEOK CHOI (Member, IEEE) received the B.S. degree from Korea University, Seoul, South Korea, in 1990, the M.S.E.E. degree from the Korea Advanced Institute of Science and Technology, Taejon, South Korea, in 1992, and the Ph.D. degree from Polytechnic University, Brooklyn, NY, USA, in 2000, all in electrical engineering. From 1992 to 1996, he was with Samsung Electronics Company Ltd., Suwon, South Korea, where he developed the 32-QAM modem for HDTV and QPSK ASIC for DBS. In summer 2000, he held a Summer Intern position at AT&T Labs-Research Shannon Laboratory, Florham Park, NJ, USA. In 2000, he joined National Semiconductor, East Brunswick, NJ, USA, where he was involved in the development of W-CDMA. From 2001 to 2002, he was a Senior Technical Staff Member with AT&T Labs-Research, Middletown, NJ, USA, where he studied MIMO systems, OFDM systems, and information theory. From 2002 to 2004, he had been with ViVATO, Inc., Spokane, WA, USA, working on smart antenna applications to CSMA protocol, Lens, and antenna/beam selection techniques. In 2004, he joined Intel Corporation, Hillsboro, OR, USA, where he studied Broadband Wireless communications systems and led the Standards team. Since 2013, he has been with Intel Labs, where he studies future wireless communications. He holds more than 70 U.S. patents.

SHILPA TALWAR (Member, IEEE) received the M.S. degree in electrical engineering and the Ph.D. degree in applied mathematics from Stanford University, in 1996. She held several senior technical positions in the wireless industry involved in a wide range of projects, including algorithm design for 3G/4G and WLAN chips, satellite communications, GPS, and others. She is currently the Director of Wireless Multicomm Systems and a Senior Principal Architect with the Wireless Communications Laboratory, Intel, where she leads a Research Team focused on advancements in network architecture and technology innovations for 5G and contributed to the IEEE and 3GPP standard bodies, including 802.16m, LTE-advanced, and 5G NR. She is also coordinating several university collaborations on 5G and leads Intel Strategic Research Alliance on 5G. She co-edited a book on 5G and has authored more than 70 technical publications. She holds more than 60 patents. Her research interests include heterogeneous networks, multi-radio interworking, mmWave communications, advanced MIMO, and full-duplex and interference mitigation techniques. She was the Co-Chair of the ICC 2014 Workshop on 5G Technologies. She has served as a Co-Editor of a Special Issue on the 5G Revolution for the IEEE SIGNAL PROCESSING JOURNAL in 2014.

SEONG YUN CHO (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in control and instrumentation engineering from Kwangwoon University, Seoul, South Korea, in 1998, 2000, and 2004, respectively. From 2004 to 2013, he was with the Electronics and Telecommunications Research Institute (ETRI) as a Senior Researcher. In 2013, he joined the Department of Robotics Engineering, Kyungil University, Gyeongsan, South Korea, as a Faculty Member, where he is currently an Associate Professor. His current research interests include integrated navigation systems, pedestrian dead reckoning, wireless positioning, filtering theory for linear/nonlinear systems, sensor-based motion detection, and LBS application systems.

BOAZ BEN-MOSHE received the Ph.D. degree in computer science from Ben Gurion University, in 2004. He was a Postdoctoral Researcher with SFU (Vancouver) from 2004 to 2005. Since 2005, he has been a Faculty Member with the Department of Computer Science, Ariel University. In 2008, he founded, with Prof. N. Shvalb, the Kinematics and Computational Geometry Laboratory, which includes several research groups in the fields of micro-robotics, wireless optimization, navigation, and medical devices. His research interests include computational geometry, navigation, mapping, autonomous, and bioinspired robotics. He was the Head of the Aerospace and Nano Satellite Research Center (founded in 2015). Since 2018, he has also been the Chair of the Department of Computer Science, Ariel University.

ALEX SCHERBAKOV received the bachelor's degree in electrical and electronics engineering from Ariel University, Ariel, Israel, in 2018, where he is currently pursuing the M.S. degree in electrical and electronics engineering. Since 2019, he has been a Research Assistant with the Kinematic & Computational Geometry Multidisciplinary Laboratory, Ariel University.



LEONID ANTSFELD received the M.Sc. degree in applied mathematics and computer science from the Technion—Israel Institute of Technology, in 2005, and the Ph.D. degree in computer science from the University of New South Wales, Sydney, Australia, in 2014. He has extensive industrial experience solving real-world complex problems by applying his research at Rafael, Intel, NICTA (Australia's Information and Communications Technology Research Center of Excellence), and the Xerox Innovation Group. He is the author of several scientific articles and patents. Since 2017, he has been a Senior Researcher with Naver Labs Europe, Grenoble, and the biggest industrial research lab for AI in France. His current research interests include sensors fusion for indoor positioning and navigation.

EMILIO SANSANO-SANSANO received the B.S. degree in industrial engineering from the Polytechnic University of Valencia (UPV), Spain, in 2002, and the B.S. degree in computer science from National Distance Education University (UNED), Spain, in 2017.

Since 2016, he has been with the Research Group on Machine Learning for Smart Environments (Giant), Jaume I University (UJI), Spain. He is currently an Assistant Professor with the Department of Industrial Systems Engineering and Design (DESID), UJI. He is also a member of the Institute of New Imaging Technologies (INIT), UJI. His current research interests include machine learning and deep learning with applications to smart environments and human activity recognition.

BORIS CHIDLOVSKII (Member, IEEE) received the M.S. degree in applied mathematics and the Ph.D. degree in computer science from Kiev State University, Ukraine, in 1984 and 1990, respectively. He was an Associate Professor with Kiev State University and an Invited Professor with Salerno University, Italy, before joining the Xerox Research Center Europe, France, in 1996. Since 2017, he has been a Principal Scientist with Naver Labs Europe, Grenoble, France. He is the author or coauthor of more than 50 patents and 100 scientific articles in international journals and conference proceedings. His research interests include machine learning, data mining, recommendation systems, time–spatial modeling, intelligent transportation systems, deep learning, and computer vision.

NIKOLAI KRONENWETT received the M.Sc. degree in electrical engineering and information technology from the Karlsruhe Institute of Technology (KIT), Germany, in 2015, where he is currently pursuing the Ph.D. degree with the Institute of Systems Optimization. His research interests include pedestrian navigation, vehicle localization, and multisensor data fusion of complementary navigation systems.

SILVIA PROPHET received the M.Sc. degree in electrical engineering and information technology from the Karlsruhe Institute of Technology (KIT), Germany, in 2014. She started to work as a Research Engineer at the Institute of Systems Optimization, KIT, in January 2015. Her research interests include navigation and guidance of unmanned aerial vehicles and sensor data fusion for indoor applications.

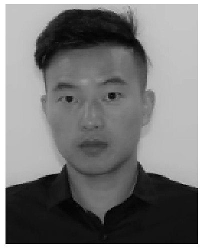
YAEL LANDAY received the B.S. degree in computer science from Ariel University, Ariel, Israel, in 2017, where she is currently pursuing the M.S. degree in computer science. Since 2017, she has been a Research Assistant with the Kinematics and Computational Geometry Laboratory, Ariel University.

REVITAL MARBEL received the B.Sc. and M.Sc. degrees in computer science from Ariel University, Ariel, Israel, in 2009 and 2017, respectively. She is currently pursuing the Ph.D. degree in computer science, with a collaboration of the Kinematics and Computational Geometry Laboratory, Ariel University. Her research interests include developing optical navigation and network optimization algorithms for mobile devices and nanosatellite laser communication. Her master thesis involved developing star-tracking algorithms for mobile devices.

LINGXIANG ZHENG received the Ph.D. degree in artificial intelligence from Xiamen University, China. He is currently a Professor at the School of Informatics, Xiamen University. His research interests include indoor positioning, mobile computing, and smart devices.

AO PENG (Member, IEEE) received the M.Sc. and Ph.D. degrees in communication and information systems from Xiamen University, Fujian, China, in 2011 and 2014, respectively. In 2015, he joined the School of Informatics, Xiamen University, where he is currently an Assistant Professor. His research interests include satellite navigation and multisource positioning and navigation.

ZHICHAO LIN received the B.S. degree in communication engineering from Zhengzhou University (ZZU), Zhengzhou, China, in 2014. He is currently pursuing the M.S. degree in information science and engineering with Xiamen University (XMU), Xiamen, China. His research interest includes indoor positioning systems.



BANG WU (Graduate Student Member, IEEE) was born in China, in 1991. He received the B.S. and M.S. degrees from the School of Geodesy and Geomatics, Wuhan University (WHU), Wuhan, China, in 2014 and 2016, respectively. He is currently pursuing the Ph.D. degree with the School of Electronic Engineering and Computer Science, Queen Mary University of London (QMUL), London, U.K.

His research interests include indoor positioning and indoor navigation, human activity recognition, the Internet of Things, and artificial intelligence.

CHENGQI MA was born in China, in 1990. He received the B.S. degree in communication engineering from the Harbin Institute of Technology (HIT), Harbin, China, in 2012, and the M.S. degree in wireless communication from Lund University, Lund, Sweden, in 2015. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, University College London (UCL), London, U.K.

His research interests include the development of indoor positioning systems, human activity recognition, and the Internet of Things.

STEFAN POSLAD (Member, IEEE) received the Ph.D. degree from Newcastle University.

He is currently an Associate Professor with the School of Electronic Engineering and Computer Science, Queen Mary University of London (QMUL), London, U.K. He heads the IoT Lab. His research interests include indoor positioning and indoor navigation, human activity recognition, the Internet of Things, ubiquitous computing, semantic Web, distributed system management, and artificial intelligence.

DAVID R. SELVIAH (Member, IEEE) received the Ph.D. degree in photonic engineering from the Trinity College, Cambridge University, Cambridge, U.K.

He is currently a Reader of optical devices, interconnects, algorithms and systems with the Department of Electronic and Electrical Engineering, University College London (UCL), London. His current research interests include machine learning, feature recognition, 3-D point cloud processing, indoor positioning and navigation, and quantum dot material characterization.

WEI WU was born in China, in 1991. He received the B.S. degree from the School of Electronic Engineering, Qufu Normal University (QNU), Jining, China, in 2015. He is currently pursuing the M.S. degree with the School of Geodesy and Geomatics, Wuhan University (WHU), Wuhan, China.

His research interests include indoor positioning and indoor navigation, noncontact measurement, the Internet of Things, and artificial intelligence.

ZIXIANG MA (Member, IEEE) received the B.Sc. degree from the Department of Geo Exploration Science and Technology, Jilin University, China, and the M.Sc. degree from the College of Geoscience and Surveying Engineering, China University of Mining and Technology, Beijing, China. He is currently pursuing the Ph.D. degree with the School of Electronic Engineering and Computer Science, Queen Mary University of London, London, U.K.

His current research interests include the Internet of Things, indoor positioning LBS, and computer vision.

WENCHAO ZHANG received the B.S. degree in surveying engineering from the China University of Mining and Technology (CUMT), in 2013, the M.S. degree in surveying engineering from Information Engineering University, in 2016, and the Ph.D. degree in signal and information processing form the University of Chinese Academy of Sciences (UCAS), in 2020. He currently belongs to the Aerospace Information Research (AIR) Institute, Chinese Academy of Science (CAS). His research interests include multi-information fusion method, integrated navigation algorithm, pedestrian autonomous positioning algorithm based on MEMS sensors, and pedestrian indoor positioning method based on inertial sensors.

DONGYAN WEI received the B.S. degree in communication engineering from the University of Electronic Science and Technology of China (UESTC), in 2006, and the Ph.D. degree in signal and information processing from the Beijing University of Post and Telecommunication (BUPT), in 2011. He is currently a Research Fellow with the Aerospace Information Research (AIR) Institute, Chinese Academy of Science (CAS). He is the author of one book, more than 30 articles, and more than 20 inventions. His research interests include indoor positioning, multisensor fusion, and positioning in wireless networks. He is also the TPC member of IPIN 2019 and the Deputy Chair of IPIN 2022.

HONG YUAN received the Ph.D. degree from the Shanxi Observatory of the Chinese Academy of Sciences, in 1995. From 1995 to 2004, he worked with the Wuhan Institute of Physics and Mathematics, Chinese Academy of Sciences. In 2004, he was transferred to the Academy of Opto-Electronics (AoE), Chinese Academy of Sciences. He is currently a Research Fellow with the Aerospace Information Research (AIR) Institute, Chinese Academy of Science. He is also involved in software and hardware design and algorithm research related to satellite navigation, multisource fusion navigation, and ionospheric detection. For many years, he has been involved in research on ionospheric radio wave propagation, GPS, Beidou satellite navigation system construction, manned space applications, ionospheric physics, ionospheric detection, and so on. He has hosted or participated in 13 national and provincial level projects, eight provincial and ministerial science and technology awards, more than 30 invention patents, and has published more than 60 articles.

JUN-BANG JIANG received the B.S. degree in computer science from the National Taiwan University of Science and Technology, Taipei City, Taiwan, in 2015, where he is currently pursuing the M.S. degree with the Department of Electronic and Computer Engineering. His research interests include smartphone-based indoor positioning, pedestrian dead reckoning, fingerprinting, and model compression.

SHAO-YUNG HUANG received the B.S. degree in electronic engineering from the Kaohsiung University of Science and Technology, Kaohsiung City, Taiwan, in 2018. He is currently pursuing the M.S. degree with the Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, Taipei City, Taiwan. His research interests include smartphone-based indoor positioning, pedestrian dead reckoning, and fingerprinting.

JING-WEN LIU received the B.S. degree in electronic engineering from the Kaohsiung University of Science and Technology, Kaohsiung City, Taiwan, in 2017, and the M.S. degree from the Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, Taipei City, Taiwan, in 2020. His research interests include smartphone-based indoor positioning, pedestrian dead reckoning, and fingerprinting.

KUAN-WU SU (Member, IEEE) received the B.S. degree in computer science from National Chiao Tung University, Hsinchu, Taiwan, and the M.S. degree from the Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, Taipei City, Taiwan, where he is currently pursuing the Ph.D. degree. He has been with Trustable Ltd., Taiwan, as a System Engineer, since 2003, and held a position as a Special Assistant to the President in eMorse Ltd., Taiwan, from 2005 to 2009, with experiences in the telecommunication industry as well as financial and Intellectual Property management. His research interests include human-centric computing, mobile UI/UX, sensor networks, cloud/edge computing, music information retrieval, social networks, and machine learning along with neural networks, fuzzy inference, and evolutionary strategies.

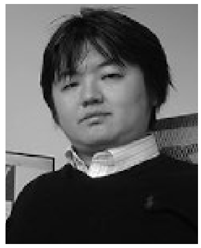
JENQ-SHIOU LEU (Senior Member, IEEE) received the B.S. degree in mathematics and the M.S. degree in computer science and information engineering from National Taiwan University, Taipei City, Taiwan, in 1991 and 1993, respectively, and the Ph.D. degree on a part-time basis in computer science from National Tsing Hua University, Hsinchu, Taiwan, in 2006. He was with Rising Star Technology, Taiwan, as a Research and Development Engineer from 1995 to 1997, and worked in the telecommunication industry (Mobitai Communications and Taiwan Mobile) from 1997 to 2007 as an Assistant Manager. In February 2007, he joined the Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, as an Assistant Professor. From February 2011 to January 2014, he was an Associate Professor. Since February 2014, he has been a Professor. His research interests include mobile service and platform design and application development of computational intelligence.

KAZUKI NISHIGUCHI received the B.E. and M.E. degrees from Kyushu University, in 2018 and 2020, respectively. His research interests include computer vision and intelligent transportation systems.

WALID BOUSSELHAM is currently pursuing the M.Sc. degree with the Department of Statistics and Applied Probability under a joint partnership degree between ENSTA Paris, which is also a French Grand Ecole and the National University of Singapore (NUS). His master thesis at NUS is about developing a Deep Learning algorithm to detect intestinal polyps.

HIDEAKI UCHIYAMA (Member, IEEE) received the B.E., M.E., and D.E. degrees from Keio University, in 2006, 2007, and 2010, respectively. From 2012 to 2014, he worked with Toshiba Corporation. From 2014 to 2018, he was an Assistant Professor with the Graduate School of Information Science and Electrical Engineering, Kyushu University. Since 2018, he has been an Associate Professor with the Library, Kyushu University. His research interests include indoor navigation, computer vision, and augmented reality.

DIEGO THOMAS received the M.E. degree from ENSIMAG-INPG, in 2008, and the D.E. degree from the National Institute of Informatics, in 2012. Since 2016, he has been an Assistant Professor with the Graduate School of Information Science and Electrical Engineering, Kyushu University. His research interests include 3-D modeling, 3-D registration, photometry, and range image.



ATSUSHI SHIMADA (Member, IEEE) received the M.E. and D.E. degrees from Kyushu University, in 2004 and 2007, respectively. Since 2017, he has been an Associate Professor with the Graduate School of Information Science and Electrical Engineering, Kyushu University. His research interests include image processing, pattern recognition, and neural networks.

RIN-ICHIRO TANIGUCHI received the B.E., M.E., and D.E. degrees from Kyushu University, in 1978, 1980, and 1986, respectively. Since 1996, he has been a Professor with the Graduate School of Information Science and Electrical Engineering, Kyushu University, where he directs several projects including multiview image analysis and software architecture for cooperative distributed vision systems. His current research interests include computer vision, image processing, and parallel and distributed computation of vision-related applications.

VICENTE CORTÉS PUSCHEL received the B.Sc. degree in electrical engineering from the Facultad de Ciencias Físicas y Matemáticas de la Universidad de Chile, in 2020. He has been working with AraraDS since the end of 2019, focusing on the research and development of indoor positioning techniques for smartphone devices.

TOMÁS LUNGENSTRASS POULSEN received the B.S. degree in mathematical engineering from the Pontificia Universidad Católica de Chile, the Ingénieur Polytechnicien (M.S. level) degree from the École Polytechnique de Paris, in 2015, and the M.S. and Ph.D. degrees in mathematics from the Pontificia Universidad Católica de Chile.

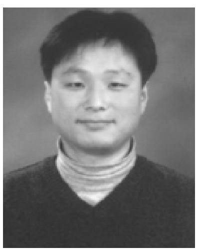
In 2016, he assumed as a Lead Data Scientist with AraraDS, Santiago, Chile, where he has focused on indoor positioning technologies and mathematical and computational tools for the digitalization of physical environments. His current research interests include camera-based quality and process control automation.

IMRAN ASHRAF received the M.Sc. degree from the Blekinge Institute of Technology, Sweden, in 2011, and the Ph.D. degree in information and communication engineering from Yeungnam University, South Korea, in 2018. He is currently working as a Postdoctoral Fellow with Yeungnam University. His research interests include indoor positioning and localization, advanced location-based services, and big data.

CHANSEOK LEE was born in Seoul, South Korea, in 1993. He received the bachelor's degree in information and communication engineering from Yeungnam University, South Korea, in 2018. He is currently working with Yeungnam University. His research interest includes pedestrian dead reckoning.

MUHAMMAD USMAN ALI received the Ph.D. degree in information and communication engineering from Yeungnam University, South Korea, in 2018. He is currently working with the Department of Computer Science, University of Gujrat, Pakistan. His research interests include indoor positioning and localization and indoor navigation.

YEONGJUN IM received the master's degree in information and communication engineering from Yeungnam University, South Korea, in 2019. He is currently working with Yeungnam University. His research interests include advanced location-based technology and deep learning.



GUNZUNG KIM (Member, IEEE) received the Ph.D. degree from Yeungnam University, South Korea, in 2018. He is currently working with the Mobile Communication Laboratory, Yeungnam University. He works in LIDAR and autonomous vehicles.

JEONGSOOK EOM received the master's degree in information and communication engineering from Yeungnam University, South Korea. She is currently working with the Department of Information and Communication Engineering, Yeungnam University. Her research interests include optics, LIDAR, and big data.

SOOJUNG HUR (Associate Member, IEEE) received the B.S. degree from Daegu University, South Korea, in 2001, and the M.S. and Ph.D. degrees in information and communication engineering from Yeungnam University, South Korea, in 2007 and 2012, respectively. She is currently working as a Research Professor with the Mobile Communication Laboratory, Yeungnam University. Her current research interests include the performance of mobile communication, indoor/outdoor location, and unmanned vehicle.

YONGWAN PARK (Member, IEEE) received the B.E. and M.E. degrees in electrical engineering from Kyungpook University, Daegu, South Korea, in 1982 and 1984, respectively, and the M.S. and Ph.D. degrees in electrical engineering from the State University of New York at Buffalo, USA, in 1989 and 1992, respectively. He is currently a Professor with Yeungnam University and also serving as the Chairman for the 5G Forum Convergence Service Committee in South Korea. His current research interests include 5G systems in communication, OFDM, PAPR reduction, and indoor location-based services in wireless communication and smart sensors (LIDAR) for smart cars.

MIROSLAV OPIELA was born in Prešov, Slovakia, in 1991. He received the B.S. and M.S. degrees in computer science from P. J. Šafárik University (UPJS), Košice, Slovakia, where he is currently pursuing the Ph.D. degree.

His research interests include smartphone-based indoor positioning and Bayesian filtering.

ADRIANO MOREIRA (Member, IEEE) received the "Licenciatura" degree (five years) in electronics and telecommunications engineering and the Ph.D. degree in electrical engineering from the University of Aveiro, Portugal, in 1989 and 1997, respectively. He is currently pursuing the Habilitation degree with the School of Engineering, University of Minho.

He is also an Associate Professor with the School of Engineering, University of Minho, and a Researcher with the Algoritmi Research Center. He co-founded the Computer Communications and Pervasive Media (CCPM) research group. He is also the Director of the MAP-tele doctoral program in Telecommunications. His research interests include mobile and context-aware computing, urban computing, human mobility analysis, indoor positioning, and simulation of wireless and mobile networks in urban contexts. His research activities have been taking place within the ubicom@uminho research sub-group, which has been focusing on the creation of technologies for smart places. In the past few years, he participated in many research projects funded by National and European programs. He is the author of several scientific publications in conferences and journals and the author of one patent in the area of computational geometry. Together with his colleagues, he won the first prize on the off-site Track of the EvAAL-ETRI Indoor Localization Competition (IPIN 2015 and 2017) and the second prize of the corresponding competition in 2016. He has been a Voting Member of the IEEE 802.11 working group, where he participated in the specification of the infrared physical layer. He is chairing the Steering Committee of the International Conference on Indoor Positioning and Indoor Navigation. He is also a member of the ICL-GNSS Conference Steering Committee and the Communications Society.

MARIA JOÃO NICOLAU graduated in systems and informatics engineering from the University of Minho, Portugal, in 1992. She received the M.Sc. and Ph.D. degrees in informatics (computer communications) from the University of Minho, in 1992 and 1995, respectively.

She is currently an Assistant Professor with the Department of Information Systems, School of Engineering, University of Minho, where she actually develops teaching and research activities in the field of communication networks and protocols. As a Researcher, she is within the Ubicomp@UMinho Research Group, ALGORITMI Research Center, University of Minho. She has been with the University of Minho as a Lecturer and a Research Staff Member since 1994. During her teaching career, she has lectured in operating systems, computer architectures, and computer networks and data communication systems. Regarding the research activity, she has participated in several research projects, supervised almost 40 postgraduate students, and coauthored more than 55 peer-reviewed articles. Her current research interests include network technologies and protocols, routing in IP networks, networks simulation, and indoor positioning.

CRISTIANO PENDÃO received the M.Sc. degree in telecommunications and informatics engineering and the Ph.D. degree in telecommunications (MAP-tele) from the University of Minho, Aveiro, Portugal, in 2012 and 2019, respectively. He has been working as a Researcher with the Algoritmi Research Center. He is currently an Invited Professor with the School of Engineering, University of Minho. His research interests include mobile computing, smart devices, and indoor/outdoor positioning systems. He has also been responsible for the development of mobile applications, for iOS and Android, in the context of research and commercial projects.

IVO SILVA received the M.Sc. degree in telecommunications and informatics engineering from the University of Minho, Portugal, in 2016. He is currently developing his Ph.D. thesis with a focus on indoor positioning of industrial vehicles based on Wi-Fi. He is also a Researcher with the Algoritmi Research Center and an Invited Assistant Professor with the University of Minho. His research interests include indoor positioning, mobile computing, and smart devices.

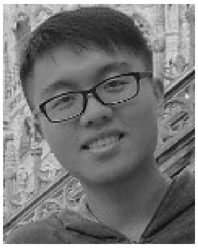
FILIPE MENESES (Member, IEEE) is currently an Invited Assistant Professor with the University of Minho, Portugal, where he is also a member of the Urban Informatics research group, Algoritmi Research Center. His research interests include indoor positioning and indoor navigation, urban and mobile computing, and analysis of human space movement. He has participated in several research projects funded by national programs, European programs (FP7 and H2020), and directly contracted by the industry. He has published his research results in different conferences and journals in the area. He has served as a member of the Technical Program Committee for several international conferences and journals. He has also co-organized several international conferences locally.

ANTÓNIO COSTA (Member, IEEE) graduated in systems and informatics engineering from the University of Minho, Portugal, in 1992. He received the M.Sc. degree in informatics and the Ph.D. degree in computer science from the University of Minho, in 1998 and 2006, respectively. He is currently an Assistant Professor with the Department of Informatics, University of Minho, where he develops teaching and research activities in the fields of computer networks and computer communications since 1992. As a Researcher, he also integrates the Computer Communications and Networks (CCN) research group, Centro Algoritmi, School of Engineering, University of Minho. He has participated in several research projects, supervised M.Sc. and Ph.D. students, and coauthored more than 60 peer-reviewed articles in the areas of indoor positioning, ad-hoc networks, vehicular networks, routing protocols, network services, quality of service, P2P, the IoT, and network management.

JENS TROGH (Member, IEEE) received the M.S. and Ph.D. degrees in electrical engineering from Ghent University, in 2014 and 2019, respectively. He has been a member of the imec-WAVES Group, Department of Information Technology (INTEC), Ghent University, since 2014. His research interests include location tracking in indoor and outdoor environments.

DAVID PLETS (Member, IEEE) has been a member of the imec-WAVES Group, Department of Information Technology (INTEC), Ghent University, since 2006, where he has also been an Assistant Professor since 2016. His current research interests include the optimization of wireless communication and broadcast networks, with a focus on coverage, exposure, and interference. He is also strongly involved in research on localization techniques and the IoT, for both industry- and health-related applications.

YING-REN CHIEN (Senior Member, IEEE) received the B.S. degree in electronic engineering from the National Yunlin University of Science and Technology, Douliu, Taiwan, in 1999, and the M.S. degree in electrical engineering and the Ph.D. degree in communication engineering from National Taiwan University, Taipei City, Taiwan, in 2001 and 2009, respectively. Since 2012, he has been with the Department of Electrical Engineering, National Ilan University, Yilan City, Taiwan, where he is currently a Full Professor. His research interests include adaptive signal processing theory, machine learning, the Internet of Things, and interference cancellation.



TZU-YU CHANG received the B.S. degree from the Department of Electrical Engineering, National Ilan University, in 2018, where he is currently pursuing the M.S. degree. His research interests include indoor positioning, machine learning, and signal processing.

SHIH-HAU FANG (Senior Member, IEEE) is currently a Full Professor with the MOST Joint Research Center for AI Technology and All Vista Healthcare, Department of Electrical Engineering, Yuan Ze University (YZU), Taiwan. He is also a Technical Advisor of HyXen and PTCom Technology Company Ltd. His research interests include artificial intelligence, mobile computing, machine learning, and signal processing. He was a recipient of several awards for his research work, including the Young Scholar Research Award (YZU, 2012), the Project for Excellent Junior Research Investigators (MOST, 2013), the Outstanding Young Electrical Engineer Award (the Chinese Institute of Electrical Engineering, 2017), the Outstanding Research Award (YZU, 2018), the Best Synergy Award (Far Eastern Group, 2018), and the Y.Z. Outstanding Professor Award (Y. Z. Hsu Science and Technology Memorial Foundation, 2019). He is also an Associate Editor of *IEICE Transactions on Information and Systems* and serves as a YZU President's Special Assistant.

YU TSAO (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from National Taiwan University, Taipei City, Taiwan, in 1999 and 2001, respectively, and the Ph.D. degree in electrical and computer engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2008. From 2009 to 2011, he was a Researcher with the National Institute of Information and Communications Technology, Tokyo, Japan, where he was involved in research and product development of automatic speech recognition for multilingual speech-to-speech translation. He is currently an Associate Research Fellow with the Research Center for Information Technology Innovation, Academia Sinica, Taipei City. His research interests include speech and speaker recognition, acoustic and language modeling, audio-coding, and biosignal processing. He was a recipient of the Academia Sinica Career Development Award in 2017 and the National Innovation Award in 2018.