11

The EvAAL Evaluation Framework and the IPIN Competitions

Francesco Potortì, Antonino Crivello, Filippo Palumbo

INSTITUTE OF INFORMATION SCIENCE AND TECHNOLOGIES "A. FAEDO" NATIONAL RESEARCH COUNCIL, ISTI-CNR, PISA, ITALY

1 Motivation and Challenges

Indoor localization systems have yet a long way to go before becoming an off-the-shelf service like outdoor localization is. Several roadblocks exist that hinder the possibility of ubiquitous and seamless positioning and navigation applications on our mobile devices. Next to technological, privacy, and standardization issues, evaluation of localization systems is one of the challenges that is currently being tackled by researchers in this field.

As in any mature technology field, common evaluation criteria are fundamental in order to add transparency to the market by defining a common performance language and eventually to build and nurture stakeholders' trust.

The problem with indoor localization systems is that they are generally complex. While in the laboratory the base techniques are individually analyzed and optimized, real working systems use many techniques that work synergically, thanks to the use of data fusion methods. At the base of these techniques, a wide spectrum of sensors work to provide raw data. On top of these techniques, applications are dedicated to a wide variety of use cases.

It is therefore not straightforward to devise ways to evaluate indoor localization systems through a series of parameters. It is not even easy to just compare two of them, because comparison is possible and meaningful on many dimensions, depending on the particular use case.

2 Background

In 2010, indoor localization had become a significant research field on its own, but it lacked of a dedicated forum. The Indoor Positioning and Indoor Navigation (IPIN) conference was born in Zurich (CH) to fill this gap. The first edition gathered about 200 attendees.

Geographical and Fingerprinting Data for Positioning and Navigation Systems. https://doi.org/10.1016/B978-0-12-813189-3.00011-3

In that same year, the EU FP7 universAAL project started its work toward creating a universal framework for developing applications for Ambient Assisted Living (AAL) and, more generally, for smart homes and smart environments, building on advances in ubiquitous computing, distributed middleware and pervasive computing and communication (Ram et al., 2013). The universAAL framework is intended to support an ecosystem of independent applications, so the problem of comparing and evaluating their performance naturally came forward.

As an answer to this demand, the universAAL project started EvAAL, with the purpose of evaluating AAL systems through competitive benchmarking (Barsocchi et al., 2013). The idea was to gather together working systems, both prototypal and mature, and independently compare their performance in one or several specific areas, with the long-term objective of creating a set of evaluation benchmarks for indoor pervasive systems. In fact, two areas were considered during EvAAL competitions, starting in 2011 in Valencia (ES): indoor localization and indoor activity recognition.

EvAAL competitions were organized yearly during the lifespan of the universAAL project, until 2013. In 2014, the IPIN conference decided to start an indoor competition on its own, building on EvAAL's experience, and the first IPIN competition was born.

In the same year, the Microsoft Indoor Localization Competition was launched, in association with the International Conference on Information Processing in Sensor Networks (IPSN) (Lymberopoulos et al., 2015). Rather than focusing on rigorous evaluation of working systems as the EvAAL and IPIN competition did, it has focused on simplicity and comparison of basic functionality, even for very prototypal systems, with the result of attracting a higher number of contestants with respect to EvAAL and IPIN.

The three initiatives previously mentioned are described in some more detail in the following.

2.1 The IPIN Conference

IPIN is the only long-lasting conference specifically dedicated to indoor localization. It is essentially dedicated to "hard-core" topics, that is, to specific low-level technology-oriented hardware and software localization techniques. It is interesting to look at the session titles along the history of IPIN conferences to look for the evolution of topics not strictly connect to low-level techniques.

The eight IPIN conferences in the years 2010–2017 had an average of 24 sessions. Of these, an average of three sessions were devoted to a topic not specifically centered on low-level software or hardware localization techniques. Table 1 lists the topics of these mid- to high-level topics.

It is interesting to note that, while since 2014 IPIN has dedicated specific sessions to discuss the results of the colocated IPIN competition, only in 2017 a session was explicitly devoted to the evaluation of indoor localization systems. This is a strong indication that the topic of system evaluation on its own has drawn attention only recently among researchers

Table 1 Mid- to High-Level Session Topics in IPIN Conferences

Year	FW	req.	apps	cntxt	comp.	maps	motion	eval.
2010	x	x	x					
2011			x	x				
2012		x	x					
2013	x	x		x				
2014	x			x	x			
2015				x	x	x	x	
2016	x	x			x	x		
2017			x	x	x	x		x

Notes: *apps*, applications; *cntxt*, context-aware systems or applications; *comp.*, IPIN competition-dedicated sessions; *eval.*, evaluation of localization systems; *FW*, frameworks and libraries; *maps*, map generation and rendering; *motion*, human motion models and monitoring; *req.*, user requirements.

and industry. This emerging attention can be partly attributed to the pioneering activity of indoor localization competitions, starting with EvAAL, and partly to the fact that while localization systems are starting to approach the market, the need for standard methods of evaluation is becoming apparent.

2.2 The EvAAL Indoor Localization Competition

The EvAAL initiative was launched by the European FP7 universAAL project in 2010 as a way of "Evaluating Ambient Assisted Living systems through competitive benchmarking." In 2011, the first EvAAL competition was held at the CIAmI Living Lab in Valencia (ES), with a single track devoted to Indoor Localization and Tracking (Barsocchi et al., 2012).

When EvAAL was born, its long-term goal was to build one or more frameworks for evaluating entire AAL systems, a huge task which was tackled step by step by considering single system modules. The first such module was in fact indoor localization. In 2012, a second track was added, namely Activity Recognition for AAL. Both tracks were present in the 2013 edition too. Due to lack of funding from the universAAL project, which ended at the beginning of 2014, EvAAL suspended its activity as competition organizer, but was careful to preserve its heritage through its web site,[1] which hosts extensive documentation of the three EvAAL competitions and of the subsequent IPIN competitions based on the EvAAL framework (Potortì et al., 2017).

During the years 2011–2013, the Indoor Localization and Tracking competition has been based on the same idea: inside a living lab, that was a small house instrumented with various sensors, a path, unknown to competitors, was drawn in advance; competing systems were given a fixed time for installing their devices in the smart home and

[1] See http://evaal.aaloa.org.

estimating in real time the position of an *actor* walking the path. The basic criteria used for the setup were:

Accommodating any Technology Competitors were free to use any technology that could be installed in the living lab and on the *actor*'s body in 1 h time.

Natural movements and environment Measurements were done in real time on an *actor* moving in a natural way, in a natural environment: he walked around the house, sit on the bed or the coach, looked for a book in a bookshelf, turned on the TV set, or the shower tap.

Reproducible path, equal for all competitors The path walked by the *actor* was precisely known (in fact, drawn step by step on the floor) and walked at precisely known speed following a chime marking each step. This arrangement allowed for an estimated path reproducibility with 10 cm error in space and 100 ms error in time, well below the accuracy required for human indoor localization.

Secret path Competitors got to know the path shape only after their own installation was complete and measurement was going to begin, because the markers on the floor were hidden by carpets before the measurement phase and only one competitor at a time was admitted to the area.

Independent measurements Competing systems had to send location estimates in real time to a central database, twice per second.

Accurately controlled timing Each competitor had 1 h for installing their hardware in the living lab and checking the communication with the measurement system provided by organizers.

Different scenarios Three scenarios were used: first, a person was located as being inside one of several Areas of Interest (AoI) or outside any AoI; second, a person was located with absolute coordinates inside the living lab; third was like the previous case but a second *disturbing actor* moved on a predefined path different from the main path.

Evaluation was based on a set of predefined metrics, both objective and subjective, the latter based on scores given by a small committee after an interview to the competitors. The final score was a weighted average of the metric scores:

Accuracy (objective, weight 0.35) The third quartile of point localization error, where error is defined as the distance from the ground truth position (the mark on the floor) and the position estimated by the competing system, computed through linear time interpolation.

Availability(objective, weight 0.20) The quote of real-time samples, produced by the competing system, that were at a distance of 500 ms from each other.

Installation complexity (objective, weight 0.10) The time taken by competitors to install their system, with a min time of 10 min and maximum of 1 h.

User acceptance (subjective, weight 0.2) Interview scoring based on characteristics like battery duration, possibility of hiding the installation in a house, need of cabling, need of periodic recalibration, and so on.

Interoperability (subjective, weight 0.15) Interview scoring based on characteristics like presence of documented API, use of a free software license, use of standard protocols and libraries, operating systems supported, and so on.

The score with the highest weight was the accuracy performance, as should be expected from evaluation metrics of a positioning and tracking system. The choice of third quartile favors result stability and credibility (Barsocchi et al., 2013), and was a prominent distinguishing characteristic of the EvAAL competitions.

The setup and evaluation criteria made EvAAL a rigorous and difficult competition, and in fact the number of attendants for the localization track was seven or eight in all three editions. Competing systems not only had to show good performance, but they had to be installed from scratch in an unknown environment in 1 h time, had to interact with an external logging system, had to work without interruption for the 10 min or so of the longest path walked by the actor. All these requirements were hard to meet for prototypal or unstable systems.

The upside was that EvAAL competitions were *realistic*. The actor moved in a realistic way in a real domestic environment and the results were gathered and displayed in real time. As a consequence, the accuracy performance was significantly lower than what you can read in academic papers, as they reflected real-life situations. From this point of view, the EvAAL competitions were a breakthrough, as for the first time they provided realistic performance measurements of indoor localization systems.

2.3 The Microsoft Indoor Localization Competition

In 2014, the International conference on information Processing in Sensor Networks (IPSN) hosted the first edition of the Microsoft indoor localization competition. The competition favors inclusion by setting a measurement environment typical of laboratory conditions, thus allowing for participation of prototypes even at a very preliminary stage. Specifically, competitors are asked to place their positioning system on a series of key points in sequence, and statically estimate the keypoints' coordinates.

The environment is not meant to represent any specific use case, and in 2014–2017 years varied from few rooms on a single floor to a 600 m^2, two-floor area. Scoring is based on accuracy only, consistently with the technology-oriented nature of the competition. The final score is based on the mean of point errors at keypoints. In the latest years, 2D and 3D tracks were considered.

On the upside, the number of participants to the Microsoft competition has been significantly higher than EvAAL's, almost always exceeding 20 participants.

3 The EvAAL Framework

As a result of the experience gained from the EvAAL competitions and the feedback obtained from the organizers and competitors, the EvAAL committee has formalized an evaluation framework (Potortì et al., 2017) to be applied to indoor localization competitions in order to measure and compare the performance obtained by the competing systems. The EvAAL framework is characterized by several *core* (the distinguishing features of the EvAAL framework) and *extended* (all adopted by the EvAAL competitions) criteria. The *core* criteria are the following:

1. *Natural movement of an actor*: The agent testing a localization system walks with a regular pace along a predefined path. The actor can rest in a few points and walk again until the end of the path.
2. *Realistic environment*: The path the actor walks is defined in a realistic setting.
3. *Realistic measurement resolution*: The minimum time and space error considered are relative to people's movement. The space resolution for a person is defined by the diameter of the body projection on the ground, which is set to 50 cm. The time resolution is defined by the time a person takes to walk a distance equal to the space resolution. In an indoor environment, considering a maximum speed of 1 m/s, the time resolution is 0.5 s.
4. *Third quartile of point Euclidean error*: The accuracy score is based on the third quartile of the error, which is defined as the 2D Euclidean distance between the measurement points and the estimated points. More discussion on this can be found in Potortì et al. (2017) and Barsocchi et al. (2013) and at the end of Section 4.2.

The *extended* criteria additionally adopted by the first EvAAL competitions are the following:

5. *Secret path*: The final path is disclosed immediately before the test starts, and only to the competitor whose system is under test. This prevents competitors from designing systems exploiting specific features of the path.
6. *Independent actor*: The actor is an agent not trained to use the localization system.
7. *Independent logging system*: The competitor system estimates the position at a rate of twice per second, and sends the estimates to a logging application provided by the EvAAL committee. This prevents any malicious actions from the competitors. The source code of the logging system is publicly available.[2]

[2] See http://evaal.aaloa.org/2017/software-for-on-site-tracks.

8. *Identical path and timing*: The actor walks along the same identical path with the same identical timing for all competitors, within time and space errors within the above-defined resolutions.

4 The IPIN Competitions

The experience of the EvAAL competitions was transferred to IPIN. The first edition of the IPIN competition was held at the IPIN 2014 Conference, located in Busan, South Korea. There were some significant differences with respect to EvAAL competitions:

No instrumentation Competitors were not allowed to instrument the competition area with their own devices.

Single technology Competition was restricted to a single technology per track.

Large area The size of the competition area was significantly larger than a small apartment.

Simple scoring Only point error accuracy was considered for scoring.

Use of keypoints Point errors where computed at a number of keypoints along the path.

Table 2 shows an overview of the number of tracks and competitors in past EvAAL and IPIN indoor localization competitions. While the numbers may look small, it is interesting to observe how such a challenging competition, requiring significant preparation effort—and significant on-site effort for on-site competing teams—keeps attracting an essentially constant number of competitors, meaning that the IPIN competition maintains its attractiveness while technology advances.

The IPIN 2014 competition, which was held in Busan (KR), was composed of two tracks: positioning through smartphone-based solution and foot-mounted pedestrian dead reckoning. Many characteristics and criteria were in common with the previous EvAAL competitions, as the IPIN competitions are based on the EvAAL framework described in Section 3.

Table 2 Tracks and Competitors in Past Indoor Localization Competition Tracks

Edition	Tracks	Competitors Real-Time	Competitors Offline
EvAAL 2011	1	7	–
EvAAL 2012	1	8	–
EvAAL 2013	1	7	–
IPIN 2014	2	7	–
IPIN 2015	3	6	4
IPIN 2016	4	14	5
IPIN 2017	4	7	9

Competitors were able to perform their own survey of the public area where the competition was held, for a whole day. This was especially useful for systems using fingerprint techniques. Since no instrumentation on the competition area was allowed, only the already deployed Wi-Fi access points could be used by competitors. Competing systems had to be carried by an actor without impairing her or his movements.

The area was a three-floor building used for conferences and big events, and the path spanned few floors, going through stairs. In such an environment, it would have been impossible to measure point localization error at each step, as it was done in EvAAL competitions. Rather, point error was measured at a series of *keypoints*, marked on the floor with adhesive plastic. The actor, rather than following a precisely defined path with steps following a chime, was free to walk in the environment, with the only constraint of passing over all keypoints in the right order. This behavior made it possible to host the competition in a public area, where other people's path could collide with the actor's one. A timestamp was collected at each keypoint to allow for independent error measurement, as detailed in Potortì et al. (2015).

The IPIN 2015 competition was held in Banff (CA). The competition consisted of two on-site and one off-site tracks: smartphone-based positioning, foot-mounted pedestrian dead reckoning positioning, and Wi-Fi fingerprinting in large environments (off-site). Tracks 1 and 2 (smartphone-based and pedestrian dead reckoning) were similar to previous year's ones. In the off-site Track 3 "Wi-Fi fingerprinting in large environments," competitors had access to a large Wi-Fi fingerprint database, to which they can apply their algorithms off-line. During this edition, 10 different teams participated in the three different tracks.

The IPIN 2016 competition was held in Alcalá de Henares (ES). The competition consisted of three on-site and one off-site tracks: smartphone-based positioning, foot-mounted pedestrian dead reckoning positioning, smartphone-based (off-site), and indoor mobile robot positioning. Tracks 1 and 2 were similar to previous years' ones. Track 3 had the goal to evaluate the performance of different indoor localization solutions based on the signals available to a smartphone (such as Wi-Fi readings, inertial measurements, etc.) that were received while a person was walking along few multifloor buildings. Track 4 was dedicated to robot positioning. The goal was monitoring the trajectory followed by a mobile robot, along a predetermined track inside an indoor area, by using a localization system installed by competitors in the navigation area and on board the robot (without interaction with the mobile robot systems). Competitors would be provided with a map of the area, while the predefined path followed by the robot would not be disclosed until the day of the competition.

The IPIN 2017 competition was held in Sapporo (JP). The competition consisted of two on-site and two off-site tracks: smartphone-based positioning, foot-mounted pedestrian dead reckoning positioning, smartphone-based (off-site), and PDR for warehouse picking. Tracks 1, 2, and 3 were similar to previous year ones. Track 4 was devoted to warehouse picking solutions based on PDR technology. It was an off-line competition based on picking data measured in a real warehouse.

4.1 Applying the EvAAL Framework to IPIN Competitions

IPIN competitions adopted the EvAAL framework by applying its *core* criteria to all tracks and part of its *extended* criteria in some tracks. We start by detailing how the *core* criteria were applied.

- *Natural movement of an actor* and *realistic environment*: In Tracks 1 (real-time smartphone-based) and 2 (real-time dead reckoning), present in all editions, the actor moves naturally in a realistic and complex environment spanning several floors of one big building. In Track 3 ("Wi-Fi fingerprinting in large environments" in the 2015 edition and "off-site smartphone-based" in 2016 and 2017 editions), the actor walks along floors of few big buildings. In Track 4, the robot moves at the best of its capabilities in a complex single-floor track in the 2016 edition, while, in the 2017 edition, the actor moves naturally in a realistic warehouse.
- *Realistic measurement resolution*: The space-time error resolution for each year's Tracks 1–3, where the agent is a person, are 0.5 m and 0.5 s, while space-time resolution for 2016 Track 4, where the agent is a robot, are 1 mm and 0.1 s (only adherence to the trajectory is considered given the overwhelming importance of space accuracy with respect to time accuracy as far as robots are concerned) and for 2017 Track 4, different resolutions are considered for each task (i.e., PDR, picking work, human moving, obstacle interference).
- *Third quartile of the point Euclidean error*: The accuracy score obtained by competitors of each track was evaluated according to the *core* criteria of the EvAAL framework related to the third quartile of point Euclidean error. It is measured using the *xy* coordinates (longitude and latitude) provided by competitors as output. Also, a penalty of 15 m is added for each floor error.

The *extended* criteria of the EvAAL framework only make sense for the real-time tracks. Here is how they were used through the IPIN competitions:

- *Secret path*: In Tracks 1 and 2, the path is kept secret only until 1 h before the competition begins, because it would be impractical to keep it hidden from the competitors after the first one in a public environment. Competitors were trusted not to add this knowledge to their systems. In 2016 Track 4 (real-time robotic), a cover was used to avoid any visual reference of the path and other visual markers, so the path was kept secret even during the competition.
- *Independent actor*: This was always used in Track 1 (smartphone-based). For Track 2, competitors themselves took the role of actors, but in 2014 and 2018 results were obtained both with competitor actor and independent actor.
- *Independent logging system*: The logging system is independent only in Track 1, while competitors in Track 2 are asked to provide a log file themselves.
- *Identical path and timing*: In Tracks 1 and 2 the paths and timing are similar but not equal, because the actor is only required to step over the key points in the right order,

without any specific constraint on the path to follow between points and the stride rhythm. In 2016 Track 4 (real-time robotic), timing and path were strictly identical as the agent was a robot, thus not affecting the final accuracy of the competitor in that context.

4.2 Discussion on the Error Statistics

From a scoring point of view, the most characteristic of the *core* EvAAL criteria is the use of *third quartile of point Euclidean error* as the metric for ranking the competing systems. This was the method used during the EvAAL competitions, which were performed on a single floor.

During IPIN competitions, which were performed on multifloor buildings, the Euclidean error was evaluated in 2D, and a penalty of 15 m was added for each wrong floor detection.

The reason behind using a point error instead of comparing trajectories (i.e., the Fréchet distance (Mathisen et al., 2016; Schauer et al., 2016)) is that the latter is less adequate to navigation purposes, for which the real-time identification of the position is more important than the path followed. The only exception was Track 4 in 2017, where the final score was the sum of several metrics, namely integrated positioning error evaluation; PDR error evaluation; picking work evaluation; human moving velocity evaluation; obstacle interference evaluation; and update frequency evaluation.

The reasons behind using the third quartile as the error metric are discussed in Potortì et al. (2017) and Barsocchi et al. (2013): first, the choice of a quantile statistics grants measurement robustness and answers the practical question of what is the maximum error for a given quote of samples; second, the choice of 0.75 as the quantile is consistent with the experimental nature of the competition, where most competing systems are not engineered well enough to be ready for the market. This is in contrast with the choice made in the ISO/IEC 18305:2016 Standard (ISO/IEC 18305:2016(en), 2016), where the considered quantile is 0.95, which is appropriate for a well-engineered, ready-to-market system, while it is excessively severe with respect to the current state of the art in indoor localization systems.

The reason for using an additive error penalty proportional to the floor identification error is a compromise between simplicity and realism. An even simpler solution would have been to adopt a spherical error, one of the metrics considered in the ISO/IEC 18305:2016 Standard. However, this is not appropriate for common multifloor buildings, where the weight of a Euclidean error is much more significant vertically than horizontally. An accurate, but much more complex solution, involves disposing altogether of the Euclidean distance and computing on a map the length of the path from the real point to the wrongly estimated point, as discussed in Mendoza-Silva et al. (2017). This solution will be considered for use in the future IPIN competitions.

5 IPIN Competing Systems

The IPIN competition is aimed at bringing together academic and industrial research communities for evaluating different approaches and envisioning new research opportunities in the indoor localization arena, where no accepted standards do yet exist. In this section, we introduce an overview of several real-time competing system, focusing our discussion on the different choices and technologies implemented by the competitors.

Along the various editions, many systems and techniques have been proposed. However, some common characteristics can be observed. We divide these similarities in two main categories: (i) raw data processing and (ii) filtering/data fusion strategy. Creating a system able to work in a real-world scenario is a big challenge and it involves several different parts, including inertial sensors for step detection purpose, map matching information, Wi-Fi and magnetic field data collection, and compass data processing. Produced data are then fused to output a series of estimated position coordinates.

Table 3 reports a selection of different real-time systems that participated in IPIN competitions. Both smartphone-based systems (Track 1) and pedestrian dead reckoning systems (Track 2) are listed, in order to highlight common modules and fusion strategies used. All systems in Table 3 were able to complete the whole path during the real-time competition. The two main fusion strategies chosen are Particle Filter and Kalman Filter,

Table 3 Some Representative Competing Systems Along Different IPIN Competitions

Edition	Competitor	Tracks	Raw-Data Modules	Fusion Strategy
2014	Kailos (Han et al., 2014)	1	Map, Wi-Fi, PDR	Hidden Markov model
2014	Hubilon (Park, 2014)	1	Map, Wi-Fi, PDR	Particle filter
2014	Spirit (Berkovich, 2014)	1	Map, Wi-Fi, PDR, Magnetometer	Particle filter
2015	MMSS (Li et al., 2015)	1	Map, Wi-Fi, PDR, Magnetometer	Kalman filter
2015	NESL (Ju et al., 2014)	2	PDR	Kalman filter
2016	Navindoor Fetzer et al. (2016)	1	Map, Wi-Fi, PDR, Magnetometer	Particle filter
2016	WiMag (Guo et al., 2016)	1	Map, Wi-Fi, PDR, Magnetometer	Particle filter
2016	NESL (Ju et al., 2014)	2	Magnetometer, Barometer, Gyroscope	Zero velocity update
2016	Sysnav (Chesneau et al., 2016)	2	PDR	Extended Kalman filter
2017	NESL (Ju et al., 2014)	1	Map, PDR, Magnetometer	Extended Kalman filter
2017	MCL[a]	1	Map, Wi-Fi, Magnetometer	–
2017	Magneto (Chesneau et al., 2017)	2	PDR, Magnetometer	Extended Kalman filter

[a] See http://evaal.aaloa.org/2017/competitors.

Table 4 Competing Smartphone-Based Systems Which Are Not Reported a Final Result

Edition	Modules	Strategies
2014	Map, Wi-Fi, PDR	–
2015	Map, Imaging	–
2016	Map, Wi-Fi, PDR	Particle filter
2017	Map, Wi-Fi, PDR	No standard fusion strategy

while most raw data modules can be categorized as: Map Information, PDR (step detection and orientation), Magnetometer, and Wi-Fi.

Table 4 reports a selection of different smartphone-based systems, which are applied to the real-time competitions but that were not able to reach a final result. We observe that the best Track 1 (smartphone-based) systems use many raw-data modules and adopt a reliable and well-known fusion strategy.

5.1 An Overview on the Internals of Real-Time Systems

Fig. 1 shows a graphical simplified overview of how the raw-data modules interact with the fusion strategy to produce positioning estimates.

5.1.1 *Raw-Data Modules*

Some typical raw-data subsystems are here given an overview: pedestrian dead reckoning, orientation, Wi-Fi, magnetic field, and map matching.

Pedestrian dead reckoning is a relative positioning module useful to estimate the traveling distance and the users' direction. In general, this module is based on the use of a combination of three sensors: magnetometer, accelerometer, and gyroscope. Accelerometer is used to detect the step event, from which speed can be evaluated. Step

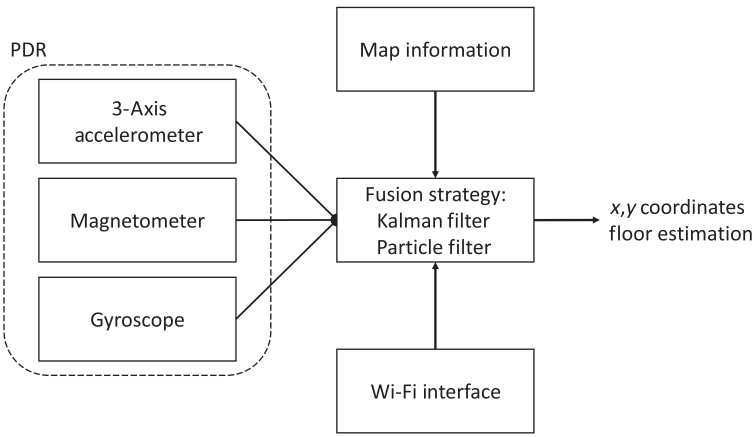

FIG. 1 A simplified overview of the interaction between raw-data modules and fusion strategy.

detection is implemented differently in the two main scenarios, that is, foot-mounted sensor and hand-held sensor. For the foot-mounted case, there is a phase when the foot is in contact with the floor for a fraction of a second, which is relatively simple to identify using a technique known as zero velocity update (ZUPT) (Foxlin, 2005). When the sensor is held in hand, as in the case of a smartphone, a spectral analysis of acceleration is used to detect low frequencies of acceleration to identify steps.

The moving direction of a pedestrian can be evaluated considering the difference between the magnetic north and the direction of the smartphone. The user orientation can be estimated using magnetic and gyroscope sensor. These values have to be corrected when the deviation errors are accumulated, due to the quality of the sensors and the behavior of the user. The main problem of these modules is the a priori knowledge of the absolute initial position. Otherwise, the usage of magnetometer and gyroscope can only produce relative position coordinates.

Wi-Fi scanning can be used for fingerprinting or for range-based methods. Both are based on RSSI measurements. Fingerprinting is based on a priori knowledge of a fingerprint database built during a site survey phase. During the positioning phase the Wi-Fi fingerprint module finds the vector of RSSI measurements for an unknown position, which is nearest to measurements stored in the database. Range-based methods use a combination of geometric techniques, essentially based on triangulation or multilateration and error minimization methods.

Similarly to Wi-Fi fingerprinting, a system can benefit from the magnetometer sensor implementing magnetic fingerprinting based on magnetic field vectors. The magnetometer of smartphones measures the magnetic field in the device coordinate system. As smartphones may be oriented arbitrarily in the user's hand, the measurements are transformed to horizontal coordinate system of the floor plan. The device orientation angles required for the transformation are estimated using the gravity vector coming from the accelerometer and the orientation coming from PDR. Magnetic fingerprinting is based on comparing the magnetic field vector measured in real-time in an unknown position with data in a fingerprint map that contains magnetic field data in known locations.

The last raw data source considered in this brief component description is the map information, being a fundamental information for navigation purpose. An efficient map matching algorithm allows to define a route of the user by matching the actual position into a building floor plan. Many improvements can be done in drawing the trajectory, for example, computing the possibility of a transition from a zone to another, to avoid crossing walls and closed door (Potortì and Palumbo, 2015; Palumbo and Barsocchi, 2014).

5.1.2 Fusion Strategies

Two different approaches are mainly used for fusing raw data: Kalman filter and particle filter.

The Kalman filter is a recursive Bayesian filter, which is optimal for Gaussian linear systems. Thanks to its easy implementation, it has been applied to many different fields for data fusion. It is an optimal estimator, assuming the initial uncertainty is Gaussian and the observation model and system dynamics are linear functions of the state. Because most systems are not strictly linear, researchers typically use the extended Kalman filter (EKF), which linearizes the system using a first-order Taylor series expansions. Kalman filter is the best option if the uncertainty in the state is not too high, which limits them to location tracking using either accurate sensors or sensors with high update rates.

A particle filter goes trough four steps, which are continuously repeated during its execution: cloud particles initialization, propagation, update or correction, and re-sampling. Initially a cloud of particles is generated in random places using a priori distribution probability assumptions. Subsequently, in the propagation stage, the coordinates and the heading of each particle are perturbed using a pedestrian motion model, using data from PDR. Other sources of information, such as magnetic data, map matching, and Wi-Fi, are then used to remove particles whose position is unlikely. Then new particles are generated based on the current distribution probability estimate to repopulate the particle cloud. Unlike Kalman filters, particle filters can converge to the true posterior even in non-Gaussian, nonlinear dynamic systems, at the price of much higher computation load (He and Chan, 2016).

6 Conclusion and Future Directions

As soon as research on indoor localization and tracking reached a sufficient number of interested research groups and industries, the need for common benchmarks has started to emerge. This need has been met by EvAAL first, then by the Microsoft and the IPIN competitions.

Comments of competitors were homogeneous during the EvAAL competitions first and during the IPIN ones next: they were impressed by the rigorous methodology used for the measurement and most said to have gained significant insight in the inner working and the potential of their own systems.

The IPIN competition is particularly interesting in that it concentrates on working systems in realistic situations, and provides realistic measures of what can be expected from a real-life system, which was shown to be significantly different from the generally optimistic figures that one can read in laboratory papers.

IPIN sessions dedicated to EvAAL have raised significant interest among IPIN attendees, especially in 2015, when a plenary session was dedicated to the competition and the general principles were illustrated.

Now that this research area approaches the market, IPIN competition will need to accompany the process and to grow by supporting modern localization systems, which exploit a variety of sensor data. For example, IPIN competitors until now have vastly ignored BLE beacons, while it is to be expected that future commercial systems will exploit their potential (Faragher and Harle, 2015; Palumbo et al., 2015; Barsocchi et al., 2017): future IPIN competitions will likely address this issue by encouraging use of BLE beacons as an important source of information in areas where little Wi-Fi coverage is available.

Another area where IPIN can experiment with new solutions is the use of a more useful metric for computing the positioning error, such as the one mentioned in Section 4.2 and presented in Mendoza-Silva et al. (2017). In general, the objective of IPIN is to define standard procedures for the evaluation of indoor localization systems, in an effort to improve over the recent ISO/IEC 18305 Standard (ISO/IEC 18305:2016(en), 2016). This effort is being coordinated by the newborn IPIN Indoor Positioning Indoor Navigation (IPIN) International Standards Committee (ISC), and should produce its first results by 2018.

The challenging nature of the IPIN competition is its most precious asset, and probably the main reason for the relatively small and constant number of competitors over the years (see Table 2). The competition tracks have adapted to technological advances since 2011, thus maintaining attractiveness, and we will keep tracking new developments. Unless confronted with significant technological or market changes, such that research interest shifts away from indoor localization, we would consider it a success to witness a similar participation in the future.

References

Barsocchi, P., Potortì, F., Furfari, F., Gil, A.M.M., 2012. Comparing AAL indoor localization systems—indoor localization and tracking. In: Chessa, S., Knauth, S. (Eds.), Evaluating AAL Systems Through Competitive Benchmarking, vol. 309. Communications in Computer and Information Science. Springer, Lecce (IT), pp. 1–13.

Barsocchi, P., Chessa, S., Furfari, F., Potortì, F., 2013. Evaluating AAL solutions through competitive benchmarking: the localization competition. IEEE Pervasive Comput. Mag. 12 (4), 72–79. ISSN 1536-1268. https://doi.org/10.1109/MPRV.2013.23.

Barsocchi, P., Crivello, A., Girolami, M., Mavilia, F., Palumbo, F., 2017. Occupancy detection by multi-power Bluetooth low energy beaconing. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–6.

Berkovich, G., 2014. Accurate and reliable real-time indoor positioning on commercial smartphones. In: 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 670–677.

Chesneau, C.I., Hillion, M., Prieur, C., 2016. Motion estimation of a rigid body with an EKF using magneto-inertial measurements. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–6.

Chesneau, C.I., Hillion, M., Hullo, J.F., Thibault, G., Prieur, C., 2017. Improving magneto-inertial attitude and position estimation by means of a magnetic heading observer. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.

Faragher, R., Harle, R., 2015. Location fingerprinting with Bluetooth low energy beacons. IEEE J. Sel. Areas Commun. 33 (11), 2418–2428.

Fetzer, T., Ebner, F., Deinzer, F., Köping, L., Grzegorzek, M., 2016. On Monte Carlo smoothing in multi sensor indoor localisation. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.

Foxlin, E., 2005. Pedestrian tracking with shoe-mounted inertial sensors. IEEE Comput. Graph. Appl. 25 (6), 38–46.

Guo, X., Shao, W., Zhao, F., Wang, Q., Li, D., Luo, H., 2016. WiMag: multimode fusion localization system based on magnetic/WiFi/PDR. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.

Han, D., Lee, S., Kim, S., 2014. KAILOS: KAIST indoor locating system. In: 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 615–619.

He, S., Chan, S.-H.G., 2016. Wi-Fi fingerprint-based indoor positioning: recent advances and comparisons. IEEE Commun. Surv. Tutorials 18 (1), 466–490.

ISO/IEC 18305:2016(en), 2016. Information Technology—Real Time Locating Systems—Test and Evaluation of Localization and Tracking Systems. Technical Committee ISO/IEC JTC 1/SC 31—Automatic Identification and Data Capture Techniques, Geneva (CH).

Ju, H.J., Lee, M.S., Park, C.G., Lee, S., Park, S., 2014. Advanced heuristic drift elimination for indoor pedestrian navigation. In: 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 729–732.

Li, Y., Zhang, P., Niu, X., Zhuang, Y., Lan, H., El-Sheimy, N., 2015. Real-time indoor navigation using smartphone sensors. In: 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–10.

Lymberopoulos, D., Liu, J., Yang, X., Choudhury, R.R., Sen, S., Handziski, V., 2015. Microsoft indoor localization competition: experiences and lessons learned. GetMobile Mob. Comput. Commun. 18 (4), 24–31.

Mathisen, A., Sørensen, S.K., Stisen, A., Blunck, H., Grønbæk, K., 2016. A comparative analysis of indoor WiFi positioning at a large building complex. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.

Mendoza-Silva, G.M., Torres-Sospedra, J., Huerta, J., 2017. A more realistic error distance calculation for indoor positioning systems accuracy evaluation. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.

Palumbo, F., Barsocchi, P., 2014. Salt: source-agnostic localization technique based on context data from binary sensor networks. In: European Conference on Ambient Intelligence, pp. 17–32.

Palumbo, F., Barsocchi, P., Chessa, S., Augusto, J.C., 2015. A stigmergic approach to indoor localization using Bluetooth low energy beacons. In: 2015 12th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pp. 1–6.

Park, Y., 2014. Smartphone based hybrid localization method to improve an accuracy on indoor navigation. In: 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 705–708.

Potortì, F., Palumbo, F., 2015. CEO: a context event only indoor localization technique for AAL. J. Ambient Intell. Smart Environ. 7 (6), 745–760.

Potortì, F., Barsocchi, P., Girolami, M., Torres-Sospedra, J., Montoliu, R., 2015. Evaluating indoor localization solutions in large environments through competitive benchmarking: the EvAAL-ETRI competition. In: Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN). Available from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=7346970.

Potortì, F., Park, S., Jiménez Ruiz, A.R., Barsocchi, P., Girolami, M., Crivello, A., Lee, S.Y., Lim, J.H., Torres-Sospedra, J., Seco, F., Montoliu, R., Mendoza-Silva, G.M., Pérez Rubio, M.D.C., Losada-Gutiérrez, C., Espinosa, F., Macias-Guarasa, J., 2017. Comparing the performance of indoor localization systems through the EVAAL framework. Sensors 17 (10). ISSN 1424-8220. https://doi.org/10.3390/s17102327.

Ram, R., Furfari, F., Girolami, M., Iba nez-Sánchez, G., Lázaro-Ramos, J.P., Mayer, C., Prazak-Aram, B., Zentek, T., 2013. UniversAAL: provisioning platform for AAL services. In: Ambient Intelligence-Software and Applications. Springer, pp. 105–112.

Schauer, L., Marcus, P., Linnhoff-Popien, C., 2016. Towards feasible Wi-Fi based indoor tracking systems using probabilistic methods. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8.