Trends in smartphone-based indoor localisation

Francesco Potortì, Antonino Crivello, Filippo Palumbo, Michele Girolami and Paolo Barsocchi
Information Science and Technologies Institute - National Research Council, Pisa, Italy
Email: {name.surname}@isti.cnr.it

***Abstract*—Indoor localisation is a thriving field, whose progresses are mainly led by innovations in sensor technology, both hardware and software. With a focus on smartphone-based personal navigation, we examine the evolution of sensing technologies in eleven leading applications. In order to select applications we choose among independently-tested prototypes, as opposed to simulation or laboratory-only experiments. To this end, we look at the best performers in the smartphone-based Tracks of IPIN competitions. This selection is particularly severe and significant, as this competition Track is performed live, without an opportunity for competitors to instrument or prepare the site or to know the path in advance and with only two attempts allowed, of which the best result is taken. An independent actor holds in hand the smartphone running the competing system, and results are downloaded from the phone immediately after the competition path is completed, without any post-processing. We show how sensing technologies have evolved from 2014 to 2019 and show a trend towards improving accuracy performance. Last, we provide insight in the role that sensors and algorithms play in the evolution of smartphone-based indoor localisation solutions.**

***Index Terms*—indoor localisation, indoor navigation, localisation competition, smartphone-based localisation**

I. Introduction

Estimating the location of a mobile target still represents a challenging task in indoor environments. While GNSS-based solutions can be successfully employed outdoor, pinpointing the location of an indoor target requires the adoption of technologies that usually cannot exploit satellites. More specifically, the existence of obstacles, the construction material of buildings and the quality of the hardware are all factors that in most cases reduce the strength of satellite signals used to compute the location or to assist the navigation of people outdoor and makes them unusable.

The objective of research on indoor localisation is creating a global environment where seamless localisation is a standard service usable by diverse devices and applications. By seamless we mean without disruption due to handoff between indoor and outdoor settings, between means of transportation and between areas with different characteristics.

The range of possible applications is huge, including personal navigation, industrial monitoring, community services, search and rescue, inventory tracking, drone and robot management, tracking in the IoT and much more. However, seamless integration between outdoor and indoor localisation systems is still in its youth and no widely deployed standard services or protocols for seamless positioning and navigation are in sight.

A promising approach for the design of indoor localisation systems is represented by the use of the sensing units available on commercial smartphones. Such devices integrate different kinds of sensors such as 3-axis accelerometer, gyroscope and magnetometer, plus barometer, light sensors and various radio frequency (RF) interfaces, with powerful processing and communications features.

This work describes the most recent trends in smartphone-based indoor localisation systems. We first show the trending research topics in order to frame the current research directions. We then survey the localisation systems evaluated during the IPIN Indoor Localisation Competition featuring a smartphone on-site Track from 2014 to 2019[1].

In particular, we consider the sensors used and the raw data processing as well as the filtering and data fusion strategy adopted. The solutions exposed in this paper were all tested in a real-world scenario and evaluated within the EvAAL framework [1]. The current trend on the design of smartphone-based systems is to combine information collected from multiple sensors simultaneously, such as magnetometer, accelerometer, and gyroscope. The combination of such sensors at high temporal resolution, combined with the use of learning algorithms, unlocks the full potential of mobile platforms for estimating the location of people indoor. Knowledge about the indoor maps is also exploited in order to reduce errors due to drift.

We present tables comparing the different solutions, we comment on trends and we finally provide an outlook on the past and the present for indoor localisation.

II. Research trends

While the potential market for location-based services is growing [2], currently no accepted solution exists which is convenient and accurate enough for general-purpose use. As of today, smartphones are the perfect candidates for personal location-based systems as they are ubiquitous and packed with strong processing, communication and sensor capabilities.

In the last ten years, smartphones have significantly increased their capabilities. Gyroscopes are today present in practically all models, magnetometers are almost equally common and barometers are not confined to the high-end market any more. Most models include a light sensor, all include Wi-Fi and Bluetooth Low-Energy (BLE) interfaces, while Ultra-Wide band (UWB) and 5G are on the way.

In the meantime, processing power, memory and battery have seen huge performance increases. Research has profited from these possibilities, so ever more sophisticated algorithms

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

and processing methods are being discovered and implemented on smartphones.

Recently, we have seen some startups offering smartphone-based ubiquitous navigation systems for personal use in indoor and outdoor environments, but with very limited market uptake and based on proprietary, non-interoperable frameworks. On the other hand, industry shows enormous interest in location-based services and limited custom solutions are being deployed. In response to this perceived interest, the research community is enlarging its objectives to missing pieces such as interoperability, standards and evaluation procedures [3], [4].

As a showcase of the research activities in indoor localisation, we look at the International conference on Indoor Positioning and Indoor Navigation (IPIN), born in 2010 and the largest of the two long-lasting conferences specifically dedicated to indoor localisation systems (the other one being UPINLBS, also born in 2010).

TABLE I
NON-CORE TOPICS AT IPIN CONFERENCES.

Year	Applications	User requirements	IPIN competition	Map generation	Human motion	Evaluation	Standards, interoperability	Security
2010	✓	✓						
2011	✓							
2012	✓	✓						
2013	✓	✓						
2014	✓		✓					
2015	✓		✓	✓	✓			
2016		✓	✓	✓				
2017	✓		✓	✓		✓		
2018	✓		✓	✓	✓	✓	✓	
2019	✓		✓	✓		✓	✓	

Since its inception, *core topics* at IPIN conferences have been low-level hardware and software techniques for positioning and navigation, which are the subjects of almost all of the about 25 technical sessions each year. As an overview of how the research horizon has grown, we look at *non-core topics* of IPIN, which are summarised in Table I.

In the last years, IPIN authors widened the range of their interests towards more high-level topics related to usage and management of localisation systems. Testing and evaluation, also in relation to standardisation is the main example, which is connected with the IPIN competitions. In fact, reaching a wide consensus on the evaluation metrics for these systems is a fundamental step towards filling the gap between prototypes and commercial systems. More recently systems interoperability has started receiving some attention. Studies on privacy and security are still very few, not enough to having dedicated a specific session to this topic until now.

this paper focuses on systems evaluation. In fact, since our aim is to provide an overview of trends on smartphone-based systems, we need a method of selecting the most significant among the thousands academic papers and the hundreds descriptions of prototypal and commercial localisation systems.

III. TRENDS IN SMARTPHONE-BASED SYSTEMS

In order to create a shortlist of significant smartphone-based systems, we concentrate on the IPIN competitions, whose purpose is comparing indoor localisation systems under realistic conditions [5]. The reason for this choice is that IPIN competitions have been the most reliable source of real-world comparison and evaluation of generic personal-oriented localisation systems based on smartphones, thanks to the rigorous approach of the EvAAL framework.

Evaluating the accuracy of an indoor localisation system means comparing the estimated position of a moving target with respect to ground truth, namely the actual position of the target along a known path, as shown in Figure 1.

In short, the EvAAL framework considers four *core* criteria:

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

and four *extended* criteria:

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

Five of the six IPIN editions 2014–2019 hosted a dedicated competition track focused on smartphone-based systems compliant to the above criteria, as discussed in detail in [6], thus providing a uniquely credible evaluation setting.

We use the results of the smartphone-based competition track along the various editions to select the most promising systems ready to be deployed in a real world scenario. The selection criteria were: i) systems robust enough to complete the whole evaluation path with a third-quartile accuracy not greater than 10 m; ii) systems that provide enough documentation explaining their inner workings. The selected systems are listed in Table II, classified with respect to used sensors and data fusion strategy. The number of competing teams in the table is relative to teams which have in fact participated and concluded it. Several teams each year apply for participation but then withdraw either before or during the competition. The low number of participants and the high number of withdrawals are both indications of the very challenging nature of this competition.

Starting in 2015, IPIN competitions have featured one *off-site* Track on smartphones, which has an interesting advantage with respect to the *on-site* one as far as comparing systems is concerned. In the off-site Track, competitors are required to implement a software-only system running at their premises

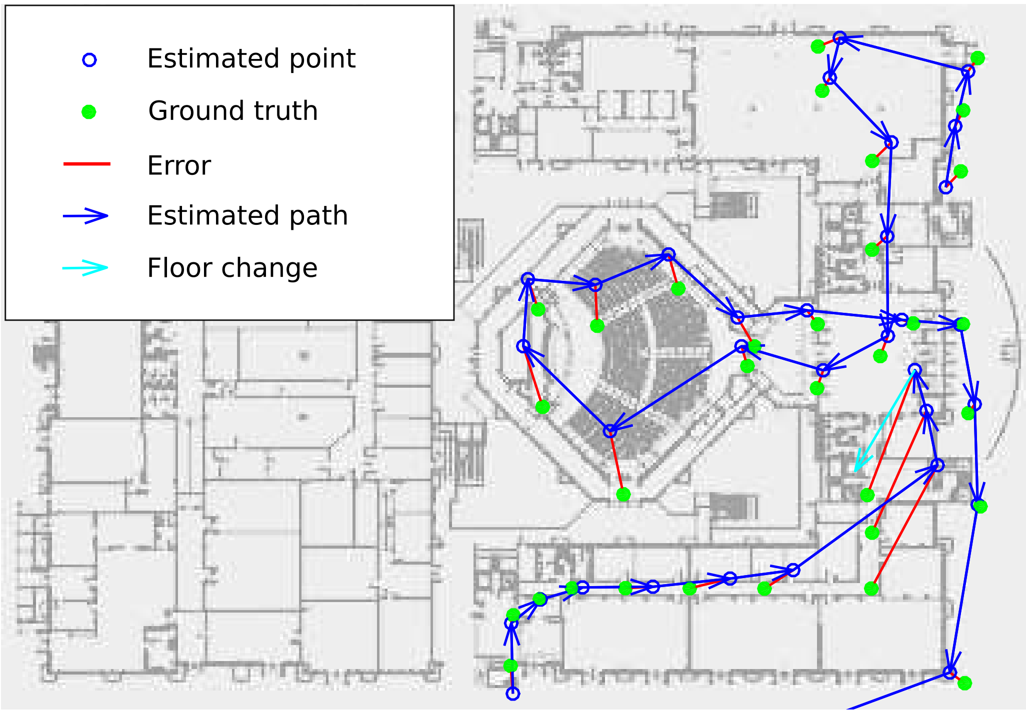

Fig. 1. Path and errors on part of the ground floor for SNU-NESL, winner of the IPIN competition 2019.

which gets input sensor data provided by the organisers. The main advantage is that the sensor data used by competitors are entirely available and thus the final results are reproducible using the same competing systems; moreover the same input data can be fed to alternative systems to experiment with different algorithms. Nonetheless, we chose to select systems competing in the on-site Track for some reasons. First, the range of usable sensors is not limited to those chosen by organisers who provide sensor input data to competitors, but the competitors can select any of those available on standard smartphones; this lack of restriction allows a more realistic view of technology advances, which is exactly what we are interested to analyse in this paper. Second, competitors in the on-site Track have deployed working systems, that is software able to run reliably for at least 20 minutes on real smartphones while providing real-time position estimates; this is not the case for off-site systems which can run on any hardware without processing power limits, and are not bound by real-time requirements. Third, the off-site Track does not prevent competitors from postprocessing their results and gives no limits on the number of attempts to obtain a good output, while the on-site Track allows two attempts and forces immediate download of computed data, so no postprocessing is done on systems. These differences explain why the on-site Track reflects more accurately the real-world performance and the current state of the art of smartphone-based systems.

From a sensing perspective, implementing a localisation system is a challenging task which usually involves the use of several sensing data sources, both hardware and software, working in real-time in a real-world environment. We distinguish between *physical sensors*, such as those measuring Wi-Fi or BLE signal strength, inertial and magnetic data, atmospheric pressure, and *virtual sensors* like optical flow, pedometer, compass, RF ranging.

Virtual sensors are set in italic in Table II. They provide indirect measurements of abstract conditions that, by themselves, are not directly measurable using a sensor. The virtual sensor output is obtained by combining sensed data, possibly from a group of heterogeneous physical sensors, and applying specific algorithms and filtering.

Note that the smartphone operating system usually gets in the way of obtaining raw data from physical sensors, requiring more or less sophisticated software tricks that need to be updated from one version to the next, and which generally do not work on iOS, which is probably the main reason why all the selected systems run on Android.

A. Data sources: maps, physical and virtual sensors

Sensor data sources are exploited to develop specific modules/subsystems as the basis of a localisation system, such as pedestrian dead reckoning, heading, radio scanning and fingerprinting, magnetic field fingerprinting, map matching.

Table II summarises the physical and virtual sensors used by the selected systems. While not mentioned in the table, all systems use maps, which provide precious information for navigation purposes.

1) RF scanning and fingerprinting: Both fingerprinting and range-based methods rely on scanning of Wi-Fi anchors (Access Points) and measurement of Received Signal Strength (RSS). Fingerprinting positioning relies on a fingerprinting database which is built during an initial survey of the site. Positioning consists of comparing the vector of real-time RSS measurement with vectors contained in the database in order to find the most similar ones. Range-based methods rely on assumed or measured path loss functions to estimated the distance from the anchors, and then apply error minimisation on multilateration or similar techniques. While the same techniques can be used for BLE, the IPIN competition settings have not provided BLE anchors for the competitors to exploit.

2) RF ranging: UWB and recent Wi-Fi versions provide RF ranging. This is not a direct measurement of a physical quantity, but the results of packet exchanges done at the protocol level by firmware, that is why RF ranging should be classified as a virtual sensors. While at least for UWB some smartphone models include this capability, the IPIN competition settings have not provided the necessary infrastructure, so competitors have not used any of them. 5G promises RF ranging too, but again the infrastructure is not there yet.

3) PDR: Pedestrian Dead Reckoning (PDR) is a relative positioning technique based on the integration of inertial sensors' output enriched with magnetometer, useful to estimate travelling distance and heading. Generally speaking, PDR systems start from an assumed known position and heading of the user, and then use the accelerometer to detect the moment a pedestrian puts her foot on the ground and use that information, together with an estimation of the step length, to compute the speed. The heading is computed from gyroscope and magnetometer outputs. There are two main PDR scenarios, depending on the location of the sensors, namely foot-mounted and hand-held. If the sensors are mounted on the foot, algorithms can exploit the moment the foot touches the floor to reset the drift errors due to integration of acceleration and angular velocity; the technique, known as zero velocity update (ZUPT) [7], significantly improves long-term accuracy of PDR for the foot-mounted case. If the sensors are held in hand, such as the case of sensors of a smartphone, one common technique to detect the steps is using the frequency spectrum of accelerometer output. One problem lies in the low quality of smartphone sensors, which are constrained by size, power footprint and price. Inaccuracy, low sensitivity and high drift are the major issues. One additional problem is that PDR requires some type of a priori knowledge of the user's initial position and heading.

4) Magnetic field: The concept of fingerprinting can be applied to any sensed quantity which can be measured on the site and is characteristic of the position. Analogously to using an RSS vector, which depends on the position of anchors and the building structure, one can use a 3-D magnetic vector to characterise a given position. The fingerprint of a given position is the magnetic vector in absolute coordinates (relative to the environment). Since the smartphone's magnetometer measures the magnetic field in its own coordinate system, it is necessary to evaluate the smartphone attitude by means of the accelerometer, which measures the gravity vector, and the heading obtained by the PDR.

5) Barometer: Barometers are useful in helping detect floor changes, be it via a lift or stairs. Signal processing is necessary because, while featuring excellent resolution, barometer readings are subject to environmental pressure changes due to weather, opening of doors and windows and air conditioning.

6) Map matching: Map matching is a fundamental part of all data fusion strategies devised by competitors, improving positioning and trajectory by estimating the probability of a transition from a zone to another, or by preventing crossing walls and closed door [8], [9]. Various strategies can be used to process an architectural map, ranging from obtaining a cleaned-up bitmap, or a vector representation, or even reducing it to a graph covering the accessible parts of the map.

Vector map representations can be enriched with metadata for navigation purpose, which can provide richer hints to the fusion algorithm. An example of this approach is introduced in [10] as a map framework, where data taken from OpenStreetMap (OSM) were used for map rendering, for routing and for aiding position estimates.

In all IPIN competitions for on-site smartphones, competitors were provided with a detailed map of the environment, as highlighted in Table II. In all cases, the map provided to competitors was at least twice larger than the real area used for the secret path, which was disclosed right at the start of the competition [1], [5].

B. Data fusion

Early solutions for indoor localisation and navigation adopted only one or two data sources to pinpoint the user position. But the current ones, including all the selected ones, exploit most or all of the sensors available on the phone and mix them using at least one of two fusion methods: Kalman filters and particle filters. As a single exception, one of the selected systems uses a hidden Markov model.

1) Kalman filters: Kalman filters were historically the first choice for fusing data coming from sensors and context information such as maps or interactions of the user with the environment. They are well understood and can be implemented efficiently, which is important for a mobile implementation. A Kalman filter is a recursive Bayesian filter used to predict the current position. It is an optimal estimator for linear systems with Gaussian uncertainties, but extended versions exist, allowing the use of strongly nonlinear constraints, such as maps. The extended Kalman filter and the unscented Kalman filter are the most common variations. Generally speaking, Kalman filters are a good choice when the uncertainty can be modelled or is small.

2) Particle filters: Particle filters are sequential Monte Carlo methods used to fuse together information from a variety of sources. Given an a priori likelihood distribution of position on a map, a cloud of particles (usually few hundreds) is generated following the distribution, and each particle is assigned a weight. The second step is propagation, where each particle moves randomly according to some movement model, Typically PDR output. Then the weight of each particle is recomputed accounting for all data which can provide a

TABLE II
MAIN CHARACTERISTICS OF REPRESENTATIVE LOCALISATION SYSTEMS – VIRTUAL SENSORS ARE TYPED IN *italic*

IPIN edition	**Competing teams**	**Competitor**	**Sensor data**	**Fusion strategy**
2014 [11]	7	Kailos [12]	Wi-Fi, IMU	Hidden Markov
		Hubilon [13]	Wi-Fi, IMU	Particle
		Spirit [14]	Wi-Fi, IMU, magnetic	Particle
2015 [11]	4	MMSS [15]	Wi-Fi, IMU, magnetic	Kalman
		Samsung [16]	Wi-Fi, IMU, magnetic	Particle
2016 [1]	6	NavIndoor [17]	Wi-Fi, IMU, magnetic	Particle
		WiMag [18]	Wi-Fi, IMU, magnetic	Particle
2017 [19]	4	NESL [20]	IMU, magnetic	Extended Kalman
2018 [21]	5	SNU [21]	IMU	Extended Kalman
2019 [22]	6	SNU-NESL [23]	IMU, magnetic	Adaptive Kalman
		STEPS [24]	*Optical flow*, *pedometer*, barometer, *compass*	Particle

likelihood map, such as RF or magnetic fingerprinting, RF ranging, barometer, map knowledge and context information. In the fourth step particles whose likelihood is too low are removed. The cycle restarts with resampling, when new particles are generated to replace the removed ones. Particle filters do not require any assumptions on the uncertainty of data, and are more useful than Kalman filters when high uncertainties and strong nonlinearities are present, in exchange for a much higher computation load [25].

IV. PAST AND FUTURE OF SENSING FOR LOCALISATION

The data gathered from the IPIN competition is limited and uneven, but it is nonetheless very precious in that it photographs the state of the art of real-world indoor localisation systems in the last several years. Here we try to sketch trends in this research area.

A. Sensing trends

RADAR was the first system proposed for personal indoor localisation which did not require specialised hardware and infrastructure [26]. RADAR opportunistically relied on received power strength measured from Wi-Fi access points.

Next came PDR, using inertial measurement units (IMU). The problem with consumer-grade IMU was drift, due to the integration algorithms necessary to obtain the position from linear acceleration and angular velocity. The ZUPT algorithm was a breakthrough for PDR, dramatically reducing the drift problem, but it can only be used if the IMU is on the foot or ankle, and thus is unusable of phones, but a magnetometer can help. In practice, for reason of price, size and power consumption, only micro electro-mechanical systems (MEMS) are used as inertial sensors for smartphone-based personal navigation systems. Currently, PDR on smartphones is based on the use of inertial sensors plus magnetometer and often barometer, and research focuses mainly on mathematical methods for getting the most out of MEMS sensors, which are generally low-accuracy and power-hungry.

Some systems then began to fuse RF information with PDR and possibly with map knowledge, usually through the use of efficient Kalman filters. The advent of powerful processors and ample memory on phones paved the way for particle filters; this is a fusion method that naturally accommodates diverse types of information and constraints, especially maps, and whose performance can naturally take advantage of improved processing capabilities. The arena which was once occupied by various flavours of Kalman filters is now dominated by particle filters and may tomorrow see the advent of neural networks, which today are mainly used as classifiers for RF fingerprinting. Future smartphones equipped with tensor processors will accelerate this trend.

RF ranging at the protocol level has not been used by any system during the IPIN competitions, because of lack of infrastructure. UWB ranging is available right now on few high-end smartphones. IEEE 802.11mc, later consolidated into IEEE 802.11-2016, has introduced Wi-Fi Round-Trip Time (Wi-Fi RTT) measurements at the protocol level, but to the authors' knowledge has had little, if any, impact on available devices until today, even if some Wi-Fi access points support it, as has done Android since version 9. 5G promises RF ranging capabilities, too. The inclusion of RF ranging in radio communication protocols witnesses the interest of industry towards applications of indoor localisation and should be closely regarded as the next possible significant step towards affordable and accurate smartphone-based personal navigation.

In Table II we can see how fusion methods profit from all the sensors present in smartphones. We observe that, of lately, systems have begun to use the virtual sensors provided by the operating systems rather than trying hard to get access to sensors at the lowest possible level. Reliance on PDR has grown, with systems appearing which make no use of Wi-Fi, and an emerging usage of vision-based methods backed

TABLE III
THIRD QUARTILE OF ACCURACY FOR THE SELECTED SYSTEMS IN THE 2014–2019 IPIN COMPETITIONS

IPIN edition	**Competitor**	Third quartile of accuracy [m]
2014	Kailos	**5.7**
	Hubilon	6.6
	Spirit	6.7
2015	MMSS	**6.6**
	Samsung	9.9
2016	NavIndoor	**5.4**
	WiMag	8.2
2017	NESL	**8.8**
2018	SNU	**6.8**
2019	SNU-NESL	**3.8**
	STEPS	7.4

by the OS. These trends can be attributed to improved OS management of sensor data, improvements in algorithms, more processing power and improved sensor hardware.

From a sensing point of view, the main limitation of sensor performance are accuracy and power consumption: improvements in these areas are bound to improve localisation performance.

B. Accuracy trends

It is difficult to gauge what is the improvement in localisation accuracy over time. While the IPIN competitions are great in exposing the state of the art and comparing systems in a given moment, they cannot give a quantitative evaluation in time, as the settings are different and not comparable each year, most notable differences including the map structure and the Wi-Fi coverage.

Anyway, by looking at the results of the selected systems shown in Table III we can get an idea of the accuracy attainable by smartphone-based state-of-the-art systems rigorously tested in the EvAAL framework. Note how vastly different these figures are from the ones found in the literature – often claiming sub-meter accuracy – which are relative to controlled conditions, careful tuning and non-uniform testing conditions.

V. CONCLUSION

Indoor localisation on smartphones is a thriving research area and is slowly gaining market interest, but real-world Indoor Localisation Systems (ILS) are few, and it is difficult to assess a technology trend by looking only at academic papers. For these reasons, in order to get a realistic view of the state of the art we looked at the IPIN competitions from 2014 to 2019.

All IPIN competitions have hosted a smartphone-based Track with consistent rules, thus allowing to compare the use of technologies over the years. We only considered stable and working ILSs, that is, those which were able to complete the competition with "reasonable" accuracy result. We excluded ILSs whose inner technology could not be assessed. The resulting set of ILSs is small, but we claim that the chosen selection criteria makes this set significant to the aim of observing technology trends.

One apparent technology trend is about increasing the importance of inertial and magnetic sensors over Wi-Fi, thus making an ILS more robust in the face of environment heterogeneity.

Another trend appears to be about relying more on the virtual sensors provided by the operating systems, like pedometer, compass, optical flow, rather than the low-level output from physical sensors like accelerometer, gyroscope and magnetometer; this may indicate that ILSs are approaching maturity and that there is increasing attention by smartphone manufacturers and operating system designers to providing high-quality base functionalities to user applications.

Lastly, there appears to be a trend towards increasing accuracy of ILSs. While this is to be expected, the numbers shown are not directly comparable and should be taken only as a general indication, because the setting of the IPIN competition is different every year. We expect that technology evolution in both hardware and software will drive performance advances confirming this trend in the next years. Specifically, we expect to see advances on the software side which build upon increasing processing power and new computation paradigms and algorithms; on the hardware side, upon improved sensor accuracy and lower power footprint.

REFERENCES

[1] F. Potortì, S. Park, A. R. Jimenez Ruiz, P. Barsocchi, M. Girolami, A. Crivello, S. Y. Lee, J. H. Lim, J. Torres-Sospedra, F. Seco, *et al.*, "Comparing the performance of indoor localization systems through the evaal framework," *Sensors*, vol. 17, no. 10, p. 2327, 2017.

[2] F. Furfari, A. Crivello, P. Barsocchi, F. Palumbo, and F. Potortì, "What is next for indoor localisation? taxonomy, protocols, and patterns for advanced location based services," in *2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE, 2019, pp. 1–8.

[3] F. Furfari, A. Crivello, P. Baronti, P. Barsocchi, M. Girolami, F. Palumbo, D. Quezada-Gaibor, G. M. M. Silva, and J. Torres-Sospedra, "Discovering location based services: A unified approach for heterogeneous indoor localization systems," *Internet of Things*, vol. 13, p. 100334, 2021.

[4] F. Potortì, A. Crivello, P. Barsocchi, and F. Palumbo, "Evaluation of indoor localisation systems: k comments on the iso/iec 18305 standard," in *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE, 2018, pp. 1–7.

[5] F. Potortì, A. Crivello, and F. Palumbo, "The evaal evaluation framework and the ipin competitions," in *Geographical and Fingerprinting Data to Create Systems for Indoor Positioning and Indoor/Outdoor Navigation*. Elsevier, 2019, pp. 209–224.

[6] F. Potortì, J. Torres-Sospedra, D. Quezada-Gaibor, A. R. Jiménez, F. Seco, A. Pérez-Navarro, M. Ortiz, N. Zhu, V. Renaudin, R. Ichikari, R. Shimomura, N. Ohta, S. Nagae, T. Kurata, D. Wei, X. Ji, W. Zhang, S. Kram, M. Stahlke, C. Mutschler, A. Crivello, P. Barsocchi, M. Girolami, F. Palumbo, R. Chen, Y. Wu, W. Li, Y. Yu, S. Xu, L. Huang, T. Liu, J. Kuang, X. Niu, T. Yoshida, Y. Nagata, Y. Fukushima, N. Fukatani, N. Hayashida, Y. Asai, K. Urano, W. Ge, N.-T. Lee, S.-H. Fang, Y.-C. Jie, S.-R. Young, Y.-R. Chien, C.-C. Yu, C. Ma, B. Wu, W. Zhang, Y. Wang, Y. Fan, S. Poslad, D. R. Selviah, W. Wang, H. Yuan, Y. Yonamoto, M. Yamaguchi, T. Kaichi, B. Zhou, X. Liu, Z. Gu, C. Yang, Z. Wu, D. Xie, C. Huang, L. Zheng, A. Peng, G. Jin, Q. Wang, H. Luo, H. Xiong, L. Bao, P. Zhang, F. Zhao, C.-A. Yu, C.-H. Hung, L. Antsfeld, B. Chidlovskii, H. Jiang, M. Xia, D. Yan, Y. Li,

Y. Dong, I. Silva, C. Pendão, F. Meneses, M. J. Nicolau, A. Costa, A. Moreira, C. D. Cock, D. Plets, M. Opiela, J. Džama, L. Zhang, H. Li, B. Chen, Y. Liu, S. Yean, B. Z. Lim, W. J. Teo, B. S. Lee, and H. L. Oh, "Off-line evaluation of indoor positioning systems in different scenarios: the experiences from IPIN 2020 Competition," *IEEE Sensors Journal*, vol. –, no. –, pp. 1–44, – 2021, special issue on Advanced Sensors and Sensing Technologies for Indoor Positioning and Navigation, IEEE early access, in print.

[7] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Computer graphics and applications*, vol. 25, no. 6, pp. 38–46, 2005.

[8] F. Potortì and F. Palumbo, "Ceo: A context event only indoor localization technique for aal," *Journal of Ambient Intelligence and Smart Environments*, vol. 7, no. 6, pp. 745–760, 2015.

[9] F. Palumbo and P. Barsocchi, "Salt: Source-agnostic localization technique based on context data from binary sensor networks," in *European Conference on Ambient Intelligence*. Springer, 2014, pp. 17–32.

[10] T. Graichen, E. Gruschka, and U. Heinkel, "A map framework using crowd-sourced data for indoor positioning and navigation," in *2017 IEEE International Workshop on Measurement and Networking (M&N)*. IEEE, 2017, pp. 1–6.

[11] F. Potortì, P. Barsocchi, M. Girolami, J. Torres-Sospedra, and R. Montoliu, "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)*, Oct. 2015.

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

[13] Y. Park, "Smartphone based hybrid localization method to improve an accuracy on indoor navigation," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2014, pp. 705–708.

[14] G. Berkovich, "Accurate and reliable real-time indoor positioning on commercial smartphones," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2014, pp. 670–677.

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

[16] A. Y. Lee, A. Kumar, P. Wilk, W. Chmielowiec, W. Jaworski, M. Skorupa, and P. Zborowski, "High accuracy indoor localization with low cost based on wireless lan, mobile sensors and floor layout," in *2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*. IEEE, 2016, pp. 1–6.

[17] T. Fetzer, F. Ebner, F. Deinzer, L. Köping, and M. Grzegorzek, "On monte carlo smoothing in multi sensor indoor localisation," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[18] X. Guo, W. Shao, F. Zhao, Q. Wang, D. Li, and H. Luo, "Wimag: Multimode fusion localization system based on magnetic/wifi/pdr," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[19] P. Barsocchi, A. Crivello, M. Girolami, F. Mavilia, and F. Palumbo, "Occupancy detection by multi-power bluetooth low energy beaconing," in *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Sept 2017, pp. 1–6.

[20] H. J. Ju, M. S. Lee, C. G. Park, S. Lee, and S. Park, "Advanced heuristic drift elimination for indoor pedestrian navigation," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2014, pp. 729–732.

[21] V. Renaudin, M. Ortiz, J. Perul, J. Torres-Sospedra, A. R. Jiménez, A. Pérez-Navarro, G. M. Mendoza-Silva, F. Seco, Y. Landau, R. Marbel, *et al.*, "Evaluating indoor positioning systems in a shopping mall: The lessons learned from the ipin 2018 competition," *IEEE Access*, vol. 7, pp. 148 594–148 628, 2019.

[22] F. Potortì, S. Park, A. Crivello, F. Palumbo, M. Girolami, P. Barsocchi, S. Lee, J. Torres-Sospedra, A. R. J. Ruiz, A. Pérez-Navarro, *et al.*, "The ipin 2019 indoor localisation competition—description and results," *IEEE Access*, vol. 8, pp. 206 674–206 718, 2020.

[23] W. Kang and Y. Han, "Smartpdr: Smartphone-based pedestrian dead reckoning for indoor localization," *IEEE Sensors journal*, vol. 15, no. 5, pp. 2906–2916, 2014.

[24] Y. Landau, B. Ben-Moshe, and R. Marbel, "Steps-indoor visual navigation framework for mobile devices." in *IPIN (Short Papers/Work-in-Progress Papers)*, 2019, pp. 299–306.

[25] S. He and S.-H. G. Chan, "Wi-fi fingerprint-based indoor positioning: Recent advances and comparisons," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 466–490, 2016.

[26] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No. 00CH37064)*, vol. 2. Ieee, 2000, pp. 775–784.