Pérez Rubio, M.C. [et al.], 2019, “A realistic evaluation of indoor robot position tracking systems: The IPIN 2016 competition experience”, Measurement, vol. 135, pp. 151-162.

Available at https://dx.doi.org/10.1016/j.measurement.2018.11.018

(Article begins on next page)

A Realistic Evaluation of Indoor Robot Position Tracking Systems: The IPIN 2016 Competition Experience

Maria Carmen Pérez Rubio[a,*], Cristina Losada-Gutiérrez[a], Felipe Espinosa[a], Javier Macias-Guarasa[a], Janis Tiemann[b], Fabian Eckermann[b], Christian Wietfeld[b], Maxim Katkov[c], Sergey Huba[c], Jesús Ureña[a], José Manuel Villadangos[a], David Gualda[a], Edel Díaz[a], Rubén Nieto[a], Enrique Santiso[a], Pablo del Portillo[a], Miguel Martínez[a]

[a] *Department of Electronics, University of Alcalá, Spain*
[b] *TU Dortmund University, Communication Networks Institute (CNI), Germany*
[c] *R&D Dept, TopoRTLS, Minsk, Belarus/Sandwich, MA, USA*

Abstract

We report a novel open competition aimed at evaluating accurate robot position tracking in indoor environments. The competition was organized within the IPIN 2016 (Indoor Positioning and Indoor Navigation international Conference). Here, we describe the competition, the competitors and their final results. The challenges of this new competition included: tracking an industrial robot following an unknown path but with a defined ground-truth, and open positioning system to be deployed on-site, with no restrictions apart from those related to safety issues. Our aim here is to provide sufficient detail to serve as a solid basis for future competition initiatives with a similar scope, using common metrics and objective evaluation procedures. In addition, the real sys-

---

[*] Corresponding author. Tel. el.: +34-91-885-6558

Email addresses: `mcarmen.perezr@uah.es` (Maria Carmen Pérez Rubio), `cristina.losada@uah.es` (Cristina Losada-Gutiérrez), `felipe.espinosa@uah.es` (Felipe Espinosa), `javier.maciasguarasa@uah.es` (Javier Macias-Guarasa), `janis.tiemann@tu-dortmund.de` (Janis Tiemann), `fabian.eckermann@tu-dortmund.de` (Fabian Eckermann), `christian.wietfeld@tu-dortmund.de` (Christian Wietfeld), `TopoRTLScrew@gmail.com` (Maxim Katkov), `Huba.est@gmail.com` (Sergey Huba), `jesus.urena@uah.es` (Jesús Ureña), `jm.villadangos@uah.es` (José Manuel Villadangos), `david.gualda@uah.es` (David Gualda), `edel.diaz@edu.uah.es` (Edel Díaz), `ruben.nieto@uah.es` (Rubén Nieto), `enrique.santiso@uah.es` (Enrique Santiso), `pablo.portillo@depeca.uah.es` (Pablo del Portillo), `miguel.martinezr@uah.es` (Miguel Martínez)

tems evaluated represent state-of-the-art performance, and thus offer interesting solutions to the problem posed in the competition.

Keywords: Indoor localization; robot tracking; open competition; standard evaluation metrics.

1. Introduction

Engineering and science competitions in a wide range of disciplines have elicited increasing interest in the international community. Hence, significant efforts have been devoted to developing challenging problems, realistic conditions, and objective evaluation procedures, and to ensure that the competitions are open to foster competitiveness and innovation.

This is why a special competition was introduced as Track 4 in the 2016 edition of the International Conference on Indoor Positioning and Indoor Navigation (IPIN). This new competition was focused on indoor mobile robot positioning, and among the most relevant challenges were: industrial mobile robot tracking a continuous trajectory, trajectory geometrically described and previously unknown for participants and identical competition conditions for all the competitors, who decide the technology for their positioning system.

This paper is organized as follows: Section 2 summarizes the related works aimed at positioning benchmarkings and comparisons. Section 3 describes the features of the competition experience. Section 4 includes the main characteristics of each system and the results obtained are compared in Section 5. Finally, Section 6 summarizes the conclusions and lessons learned.

2. Related work

There is a long tradition of robotics-related competitions, such as the Robot World Cup (Robocup) [1, 2], an annual international robotics competition launched in 1997 which has evolved into two complementary categories: the physical robot league and the software agent league. The Robot Vision Challenge [3] is another well established competition that has been running since 2009, which focuses on place recognition and object categorization from the visual information recorded on a robotic mobile platform. Other examples include the Urban Search and Rescue (USAR) competition, [4, 5], or the AUVSI (Association for Unmanned Vehicle Systems International) SUAS (Student Unmanned Aerial Systems) Competition for UAVs (Unmanned Aerial Vehicles) [6]. These competitions play an important role in the development of artificial intelligence (AI) and robotics, as explained in [7] and [8], but none of them focus on indoor robot positioning.

However, there are several other competitions aimed at indoor positioning [9, 10] that present different approaches for people [11, 12, 13] or robot [14, 15] indoor localization. Most of the indoor positioning competitions consist of locating a person in a discrete set of predefined positions in a complex indoor environment. For instance, this is the objective of the Microsoft indoor localization competition [10, 16, 17], or the EvAAL (Evaluating Ambient Assisted Living Systems through Competitive Benchmarking) localization competition [9, 18].

The Microsoft indoor localization competition in IPSN 2016 was a 2-day event, with two different categories (infrastructure-free and infrastructure based). On the first day, participants were given 7 hours for their system setup and calibration. The evaluation area consisted of two $10m \times 9m$ rooms, and a hallway between the two rooms (measuring $10m \times 4m$). The systems were evaluated based on the average location error across 20 predefined evaluation points. The official evaluation was based on a manual process, but [17] also considered the possibility of performing an automatic evaluation using the EVARILOS Benchmarking platform [19, 20]. The competition described in [21] also used an automated benchmarking infrastructure, obtained by means of a robotic mobility platform that was positioned at each static evaluation point. The results obtained by participants achieved accuracies in the meter range. The sensing technology and equipment used (RF) were common to all participants, who were able to remotely deploy their localization solutions by code upload.

The EvAAL competition was launched in 2011 [22] with the goal of enabling a comparison of different Ambient Assisted Living (AAL) solutions and experimenting with benchmarking and evaluation methods [23]. In [18], the evaluation metrics were based on accuracy, computed by comparing the competing systems measurements against the ground-truth. The error was defined as the Euclidean distance between the ground-truth positions and the estimated ones generated by competing systems. In order to rank the competing systems' results, the Cumulative Distribution Function (CDF) for the third quartile (75^{th} percentile) was used. The CDF provides information on accuracy and precision, and, at the same time, it allows an easy numerical and visual comparison between different strategies.

In 2014, the EvAAL competition was integrated in the IPIN 2014 conference and was named the *IPIN competition*. It was divided into three tracks, the objective of which was to obtain the position of a trained actor at a set of predefined points inside a large, public indoor area, without including any additional instrumentation in the competition area. A review of the EvAAL benchmarking framework is described in [24].

3. Indoor Robot Positioning Competition

In the 2016 edition of the IPIN competition, an innovative track was introduced: Track 4, aimed at indoor mobile robot positioning. Participants had to track a mobile robot along a continuous trajectory which was the same for all participants, and was not known in advance. Final scores were based on the accuracy of the position estimates provided by the competitors, as explained in Subsection 3.5. There are several differences between the previously cited competitions and the IPIN Track 4, as summarized in Table 1. In contrast to other competitions, the IPIN Track 4 considered a continuous trajectory to be tracked, instead of evaluating discrete predefined key positions. Moreover, the predefined trajectory was performed by a robot, not a person, so that the trajectory positions and robot speed were identical for all competitors. Participants provided both their own custom hardware, which had to be deployed and calibrated in a constrained time, and their algorithmic approaches to generate the estimated position of the robot.

One of the reasons for designing this new IPIN track was to create a competition scenario that is closer to industrial needs. Hence, it combines aspects such as: tracking a commercial autonomous guided vehicle (AGV); non-constant velocity programmed for the AGV (even higher than the nominal one in short time intervals); provision of elements for sensor deployment, installation and calibration; no restrictions on sensor technology or allowed devices; and a real scenario which was easily scalable. The competition design includes the availability of a ground-truth independent of the external sensor system. The IPIN Track 4 competition also closely reflected academic and scientific interests, since it was aimed at offering an educational tool and helping students to gain hands-on experience of creativity while also allowing for realistic evaluation of state-of-the-art solutions.

Competition	Year	Categories	Teams-Interested/ Participants	Setup Time	Evaluation Area	Continuous/ Discrete	Evaluation Metrics	Best Accuracy
Microsoft indoor localization competition [10, 16, 17]	2014	Infraestructure based	21/16 (76.2%)	7h (previous day)	Two rooms and the small hallway surrounding them (aprox. 230m^2).)	Discrete (20 predefined evaluation points)	Room/zone level accuracy and absolute accuracy.	0.72m
		Infraestructure free	15/9 (60.0%)					1.6m
	2015	Infraestructure based	30/19 (69.3%)					0.2m
		Infraestructure based	30/19 (69.3%)					1.2m
	2016	2D (available signals WiFi and FM, report 2D positions)	22/13 (59.1%)				Positioning accuracy.	1.2m
		3D (deploy custom hardware, provide 3D positions)	27/21 (77.8%)					0.16m
Evaluation Ambient Assisted Living System (EvAAL) [22, 25, 23, 18]	2011	Indoor localization and tracking	6/6 (100%)	3h	CIAmI Living Lab (aprox. 90m^2)	Discrete (5 areas of interest)	Weighted sum: Accuracy, installation complexity, user acceptance, availability and integrability into AAL systems.	7.14 (score)
	2012	Indoor localization for AAL	8/7 (87.5%)	60min	Smart House Living Lab (ETSIT UPM)	Continuous (2Hz)		7.70 (score)
	2013	Indoor localization for AAL	7/7 (100%)					7.21 (score)
IPIN competition	2014	Lacalization and activity recognition for AAL				Discrete (predefined points)	3^{rd} quartile of error.	
		RF-based indoor localization solutions in public spaces (EVARILOS)		Not limited but considered in metrics	iMinds test facility in Ghent, Belgium	Discrete (10 or 25 evaluation points)	Based on point/room level accuracy; latency or delay of location; energy consumption; interference robustness; set-up overhead; installation time; configuration complexity.	
		RF-based indoor localization algorithms (EVARILOS)			Remote access. EVARILOS experimental facilities at TU Berlin and iMinds		Based on point/room level accuracy; latency or delay of location; interference robustness.	
	2015	Smartphone based positioning	4/2 (50%)		The Banff Centre, Canada	Discrete (predefined points)	3^{rd} quartile of error	6.6m
		Foot-mounted PDR positioning	2/1 (50%)					5.4m
	2016	Smartphone based positioning	6/6 (100%)		School of Engineering, University of Alcala			6.6m
		Foot-mounted PDR positioning	8/5 (62.5%)					5.4m
		Robot positioning competition	4/2 (50%) (+2 off-track)	30(45)min	Previously unknown trajectory in a 12x6m area	Continuous		0.1m

Table 1: Comparison of contemporary indoor positioning competitions.

3.1. Robot

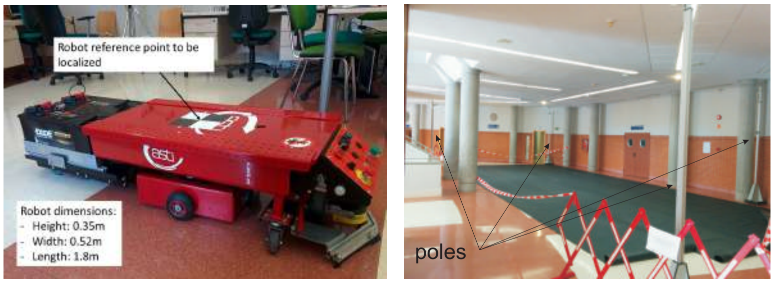
The robot unit is a Standard Easybot from ASTI international company [26]. A visual positioning label placed on the robot defined the reference point to be tracked by competitors (see Fig. 1.a). The robot mechanical configuration and wheeled system provide it with full maneuverability in such a way that the traction module can freely move in any direction. Its dimensions are $1800mm \times 520mm \times 350mm$, and its nominal speed is $0.67\frac{m}{s}$, although higher velocities can be programmed for short time intervals.

The Easybot platform tracked a magnetic tape deployed on the floor, guided by feedback provided by a magnetic detector and the corresponding closed-loop control. A black cover of $14m \times 6m$ prevented any visual reference to the magnetic path (Fig. 1.b).

3.2. Ground-truth

The competition was held at the Engineering School of the University of Alcalá, using a scenario that consisted of an area measuring $12m \times 4m$ (a 360^o photosphere picture of the location can be viewed at [27]).

The magnetic path comprised a closed route that included longitudinal and circumference sections arranged alternately. The magnetic tape was placed



(a) ASTI robot.

(b) Navigation area.

Figure 1: System set-up for the IPIN 2016 Track 4 competition. The robot (a), follows a predefined path (see Fig. 2), identical for all competitors, which is hidden by a black cover (b).

along a trajectory that had been previously drawn according to a geometrical description. This strategy ensured that the ground-truth was precisely defined and identical for each experiment (see Fig. 2). The path length was 32.84m, contained within the scenario area, and the robot followed this path twice, resulting in a full trip of 65.68m. The maximum linear speed for the first robot lap was 0.5m/s, whereas in the second lap, the speed was 0.8 m/s within the straight path interval. The speed was automatically reduced in non linear sections of the path, and the trip time was around 3 minutes.

3.3. Restrictions on the Positioning System

Participants could decide both the type and number of sensor elements and also had to comply with the competition safety rules. Four poles were placed around the navigation area to allow participants to attach their sensor units (where necessary), and an additional pole could be located at the reference point on the robot but with no interaction with its power, electrical, electronic, or safety systems. The poles could be used to attach the sensor units at the desired height (with a maximum of 3.15m) and to plug them in. There was no limitation in the number of sensors that could be affixed to the poles, but they could not exceed 3 kg in weight nor 20 cm in height. Direct *Line Of Sight* (LOS) with at least one of the poles was ensured throughout the trajectory.

Three reference points in the scenario, with known (x, y) coordinates, were provided to the competitors to allow calibration of the positioning system, one of them being the start/stop point at $(0, 0)$.

3.4. Additional Aspects

After checking the participants' positioning systems to verify their compliance with the safety, size, and weight rules established by the organizers, the participants were given up to 45 minutes to assemble, mount and calibrate their systems. They were required to report the consecutive points of the robot trajectory at least every 0.1 seconds (minimum frame rate). Each team had to provide the position information in a plain text file with three columns: x, y

coordinates in millimeters with respect to the known initial robot position, and the timestamp in milliseconds. Every line in the text file corresponded to a new estimated position. All the measurements had to be submitted by email to the organizers in a single file, within two minutes of the end of the competitor test.

The detailed competition rules were published on the IPIN web page [28].

3.5. Metrics

The competition requirement of tracking the precise robot trajectory created two important challenges with respect to the evaluation metrics: The first implication was that a consistent and sufficiently precise ground-truth position was required for comparison with the competitors' results. The second implication concerned the need to handle timing issues in order to provide a consistent timeline for position evaluation. For our purposes, having an accurate ground-truth timing is not required.

Our solution to the first implication was to propose a predefined, geometrically modeled robot trajectory, as stated above (see Fig. 2). The fact that the robot had a magnetic guidance system ensured sufficient precision for the comparison task. The systematic error due to robot characteristics was negligible and the same for all the competitors.

The solution to the second implication was to provide a "timing start" signal, and to design an evaluation strategy that did not require an accurate timing alignment between the competitor's results and the ground-truth. In addition, the fact that the ground-truth trajectory was geometrically defined contributed to the suitability of the evaluation approach.

With respect to accurate timing, we aimed to avoid the requirement of having a precise time synchronization between the robot and the competitor's systems, to reduce the complexity of the overall competition infrastructure. However, we still had to guarantee an accurate estimation of the evaluation metrics, which was more complex as we did not have the timing synchronization available. In our case, this accurate estimation was possible due to two main aspects: a) The ground-truth trajectory was geometrically defined, thus we knew in advance the

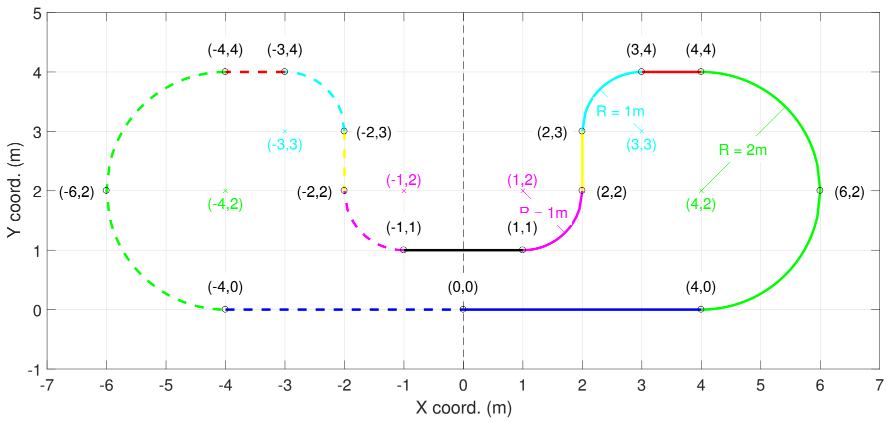


Figure 2: Ground-truth trajectory and sections into which it was divided for positioning error evaluation.

reference positions, and their time sequence; b) The evaluation strategy took into account this time information (time sequence), and the performance calculations considered cases in which “outliers” (measures that are very far away from the reference positions) could occur, which could lead to wrong estimations of the distance error.

Evaluation was based on the localization error, i.e., the Euclidean distance between the ground-truth positions and the estimated ones obtained by the participants. In order to achieve accurate error estimations, the ground-truth trajectory was divided into 13 sections, as shown in Fig. 2, each of which was modeled by a known continuous mathematical function.

The estimated robot positions were processed sequentially, comparing them against the “correct” section of the ground-truth trajectory, even if an outlier appeared. For each estimated position (x_e, y_e), the most probable section to which the measurement belonged was selected based on the estimated coordinates and considering the section in which the previous estimation had been located.

Given an estimated position, we considered that it was an outlier if its Euclidean distance to an incorrect section was lower than to the correct one. In our approach, outliers were detected taking into account the previous measurements, as shown in Fig. 3. Given the estimated position (x_e, y_e), if the previous measurement was (x_a, y_a), the correct section was the nearest one (see Fig. 3.a), whereas if the previous measurement was (x_b, y_b), the position (x_e, y_e) was detected as an outlier, and the Euclidean distance was computed against the correct section instead of against the nearest one (see Fig. 3.b).

Taking into account this information, section selection was limited to the current section and the immediately following one. This restriction significantly improved the correct detection of outliers. Once the most probable section was chosen, the Euclidean distance between the estimated measurement and the nearest point in the selected section was computed. In order to avoid possible errors in the points close to the limits between two sections, the Euclidean distances to the previous and following sections were also computed, and the lowest value was selected.

Given an estimated measurement (x_e, y_e) for horizontal straight sections, the nearest point was the one with the same $x = x_e$ coordinate. Similarly, for vertical straight sections, the nearest point was the one with the same $y = y_e$ coordinate. Since curved sections were defined as circumference segments, the nearest point for these was obtained as the intersection between the circumference and the straight line between (x_e, y_e) and the corresponding circumference center (x_c, y_c).

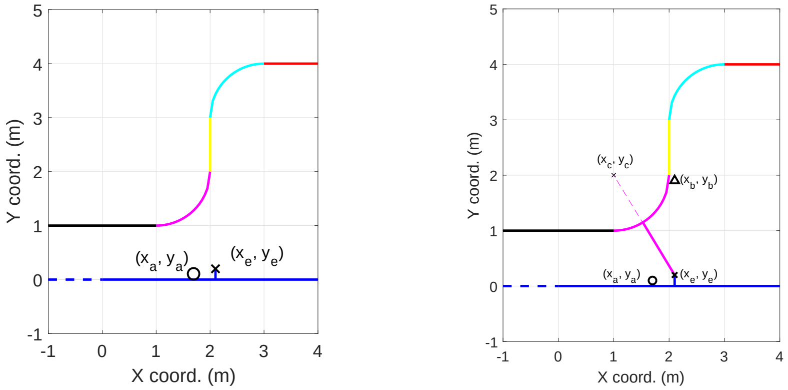
The final accuracy metric was computed as the localization error at the third quartile (75% percentile). In the case of a tie, the error at 50% of the CDF would be evaluated. A detailed discussion of the use of the third quartile of error (which coincides with the CDF at 75%) is given in [9].

More information on practical issues concerning Track 4 can be found in [29].

4. Evaluated Systems

Four groups participated in the first edition of the IPIN Track 4 competition. It should be borne in mind that this new competition implied several important challenges: tracking an industrial robot following an unknown path but with a mathematically described ground-truth; an open positioning system (related to technology and number of devices) with no restrictions except those concerning safety issues; a constrained time slot for deployment and calibration of the sensor units; uncertainty regarding the scenario (i.e. an environment with natural and/or artificial lighting); and the need for real-time processing.

Among the participants, two were the so-called *in-track* competitors, who officially entered the track as competing teams; and the other two were *out-of-track* competitors, who were not allowed to officially compete for the prize as they used procedures that did not strictly comply with the competition rules with respect to positioning system setup and calibration. The technologies used by the teams included Ultra-Wideband (UWB), ultrasonic signals, and a laser scanner. From the information collected, participants used their own



(a) If the previous measurement is (x_a, y_a), the blue straight segment is the correct one.

(b) If the previous measurement is (x_b, y_b), the magenta curved segment is the correct one.

Figure 3: Example of selection of the “correct” segment (example (a)), detection of outliers (example (b)), and distance calculation for an estimated position (x_e, y_e).

(a) Node hardware (b) Competition setup with battery and relay for pole mounting

Figure 4: Hardware used in the competition by the ATLAS team. Note the orientation of the anchor node antennas. The antenna of the nodes is mounted upwards, with the flat side facing the competition.

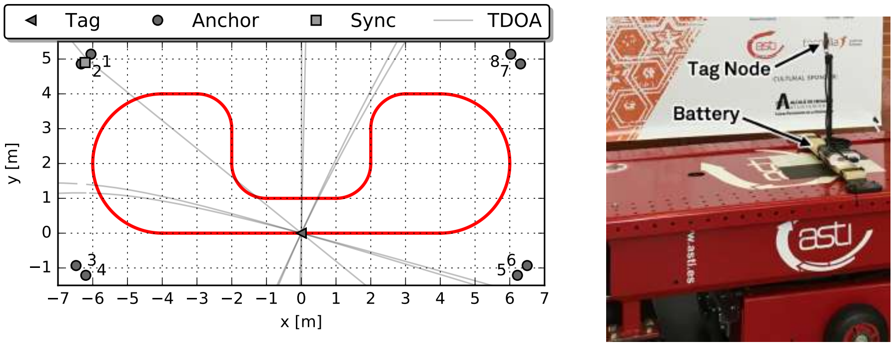
algorithmic approaches to generate the estimated positions that were reported to the organization for comparison with the ground-truth.

*4.1. ATLAS Team (*in-track *section)*

ATLAS is a time-difference of arrival (TDOA) localization system based on ultra-wideband (UWB). System design focuses on modularity, scalability [30], and ease of use. Therefore, the system is structured in as few as four components: The wireless localization tags to be localized, the wireless localization anchors that receive messages from the tags, the synchronization node, and the localization server.

All wireless localization nodes use the same hardware, shown in Fig. 4. The hardware design is based on the *DWM1000* module from *Decawave* [31], using a modern ARM-based processor as a host controller. The power supply and host communication are handled over a serial USB interface. To facilitate comparability and reproducibility, the hardware design files are provided in [32]. All nodes also share the same firmware, with the emphasis on shifting complexity from the distributed system components to the central localization server.

In the context of this competition, the team added Ethernet relays using *socat* to cope with the physical dimensions of the competition area. Note that the backbone does not distribute a common clock.



(a) Anchor distribution in the competition setup

(b) Tag on robot

Figure 5: Competition setup. Note that the ATLAS system used eight anchor nodes distributed in pairs of two anchors per pole.

The central application handling all incoming and outgoing packets is the ATLAS localization server (source code is provided in the authors' study [33]).

Due to the individual clock drift of each anchor, accurate clock synchronization is required for precise localization. Therefore, wireless clock synchronization is achieved through a dedicated node. The known periodicity of those synchronization packets enables the localization server to reconstruct the individual relative clock offsets and drifts of the anchor nodes. Based on the received extended unique identifier (EUI), packet number and system clock, the localization server assembles corresponding samples.

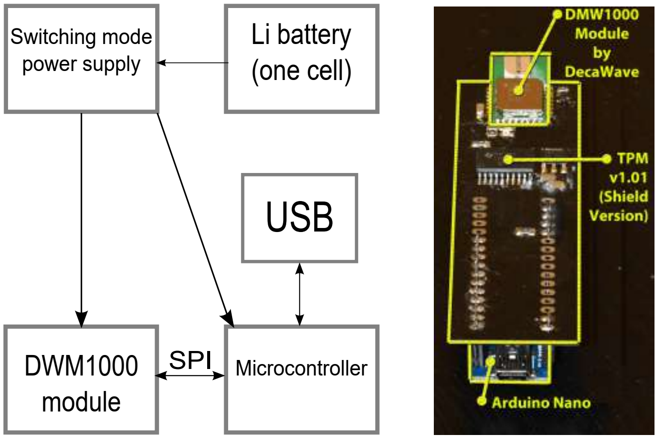
An Extended Kalman Filter (EKF) is used for position estimation. A detailed description of the positioning is given in [34]. However, some changes were introduced to optimize the competition setup. The state vector was reduced to a two-dimensional form, as the height of the robot was known in advance. The first tag was selected as the reference tag for TDOA positioning during this competition. To improve reliability, only one positioning sample was processed, when all eight anchors had received the mobile tag.

The setup in the competition area featured a set of eight anchor nodes and a synchronization node, as depicted in Fig. 5. A pair of two anchors in each corner was chosen to improve the overall accuracy through redundancy. In a post-setup calibration step, a second tag with a known position was inserted into the system. The localization server calculated and compared the expected TDOAs to the measured ones for this calibration tag. Based on these differences, a static offset was added to the TDOAs of each anchor node. In this competition setup, the calibration tag was placed at $x = 0$ m and $y = 2$ m. A set of 200 calibration measurements was obtained before the calibration step was finished and the calibration tag removed. This calibration step was mainly aimed at eliminating static offsets when propagating the synchronization signal from the synchronization node to the anchor nodes. A previous work [34] showed that static TDOA offset calibration helps to improve the overall system accuracy.

*4.2. TPM Team (*in-track *section)*

TPM is a three dimensional positioning system based on the DWM1000 UWB module by Decawave. The system is based on anchor/tag communication. Prior to use, the anchors must be installed and initiated. Installation of the wireless system requires positioning the anchors in stable, predetermined locations, preferably 2 meters away from walls, and more importantly, from metal objects. The exact location of each anchor must be used for tag position calculation, although a self-positioning option is available for easier, albeit less accurate measurements. The self-positioning technology and wireless option of this system provides ease of use and usage mobility. Each board can be used either as a tag or as an anchor.

The TOA location technology used helps to eliminate wires but has a negative impact on the update rate. The maximum update rate of this system is up to 100 Hz per tag. During the competition, 5 anchors and 1 tag were used with a 20 Hz update rate. The gate node (5^{th} anchor) was not used for measurements, but to gather information from all the anchor/tag communications in order to locate a tag. Tag position is calculated using the multilateration method. The system requires at least 3 anchors to operate, and each additional anchor used improves the achieved precision, but lowers the update rate, since the system



(a) TPM board block diagram.

(b) Anchor/Tag hardware.

Figure 6: TPM block diagram and node hardware.

only allows a tag to communicate with one of the anchors at a time.

The TPM hardware is based on an Arduino Nano board with an integrated DWM1000 module by Decawave (see Fig. 6.a for a block diagram of the system and Fig. 6.b for a photo of the implemented hardware).

The self-positioning method allows users to let the system calculate all the distances between each anchor, and build a 3D field map based on the collected data. The (x, y, z) location coordinates of each anchor will not be related to the ground truth, but if 3 anchors are later started, the rest of the system recalculates the data based on the real positions. In the case of a 5 or 20 anchors system, only three anchors are required to obtain exact data to calculate the entire 3D field. An additional real position of any anchor will increase the final accuracy. Deploying more anchors improves the system for places where the exact location is hard to determine (different floors, walls, etc.). Whenever the location does not need to be related to real a geo-location, three anchors must be semi-initiated with $(0, 0, 0)$; $(0, 0, z)$, and $(0, y, z)$ coordinates where y and z are calculated by the system itself. During the competition, three initial anchors were used to build up a plane: $CP1(0, 0, 0)$, $CP2(X, 0, 0)$ and $CP3(X, Y, 0)$ (see

Fig. 7).

(a) Calibration Points (CP) during TPM setup. (b) Anchor hardware.

Figure 7: TPM competition setup.

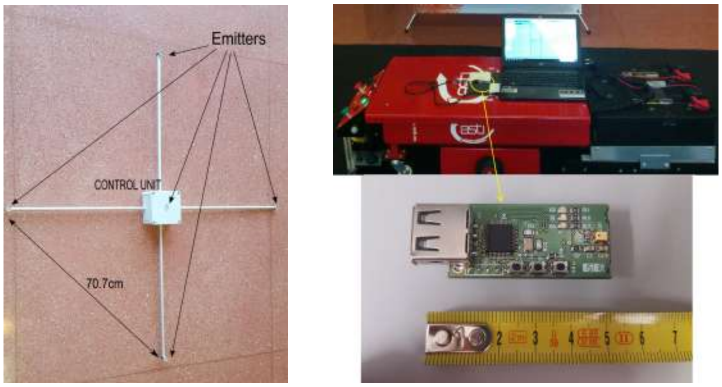
The UWB system works with or without LOS. As a second option, accuracy drops proportionally to the size of an object between that of a tag and each anchor. All objects located near the tag/anchor also create interferences. If high accuracy is not a primary goal, all anchors can be deployed at any place where measurements must be taken.

*4.3. LOCATE-US Team (*out-of-track *section)*

The LOCATE-US system is based on a set of low cost ultrasonic local positioning systems (U-LPSs) and a small acquisition system that is placed on the robot reference point to be located. The acquisition system sends digitized ultrasonic signals over a USB connection to a portable device where TDOA estimations are computed to obtain the position using hyperbolic trilateration.

Every U-LPS consists of a modular and easy to deploy structure based on five Prowave 328ST160 ultrasonic transducers [35] (see Fig. 8.a), and covers an approximate area of $30m^2$ when installed on the ceiling at a height of $3.5m$. The emission is controlled by a LPC1768 microcontroller [36] that allows remote configuration of ultrasonic transmissions in terms of sampling frequency, modulation schemes, and signals to be emitted. The emissions are encoded with 255-bit Kasami sequences, so as to obtain a more accurate determination of the TDOA and clearly identify the signals associated with each beacon. The Kasami codes have been BPSK modulated with two periods of a sinusoidal carrier at 41.67 kHz (the Prowave transducers provide a linear phase response over an 8 kHz bandwidth around 40 kHz). Since only one Digital to Analog Converter (DAC) is available in the microcontroller, the codes associated with each beacon are transmitted one after the other, each of them using a $20ms$ time slot. Thus, the time interval between two consecutive emissions of the same code is $100ms$. Three U-LPSs were placed on the ceiling to obtain good accuracy within the IPIN Track 4 competition area. All U-LPSs emit simultaneously, although there is no need for synchronization between them or with the receiver on board the robot. Since the emitted signals were encoded with different Kasami codes, low mutual interference and emitter identification are assured, even in cases where the robot receives signals from more than one U-LPS. The U-LPS positions were obtained during the set up stage through manual calibration, using two of the reference points provided by the organization. This calibration process began by projecting the beacons of each U-LPS onto the floor using a plumb-line. Then, the distances between the projected points and the reference positions were obtained using a laser distance meter. Finally, an optimization algorithm provided the 2D position of each beacon using the measured distances. In addition, the value for the height of each U-LPS was obtained by the laser meter in order to determine the 3D position of each transducer.

The acquisition module (see Fig. 8.b) includes a MEMS SPU0414HR5H-SB microphone [37] with an adequate bandwidth at $41.7kHz$ and a STM32F103 microcontroller. The ultrasonic signals captured by the microphone are high-pass filtered and amplified or attenuated through a programmable gain module, to obtain an adequate signal level. The microcontroller digitizes the signals at a sampling rate of $100kHz$, fills a buffer with 13000 samples ($0.13s$ of the ultrasonic signal), and sends them over a USB link to the portable device. Then, a new acquisition starts. The buffer size ensures that at least one complete code pattern from each transmitter is received. Locate-US is intended for application in smartphone location tasks, so as to offer Location Based Services (LBS) to their users (see [38] for more information). Nevertheless, for simplicity, a laptop



(a) Portable beacon unit (b) Acquisition module

Figure 8: Hardware used in the competition (LOCATE-US team).

was employed during the competition, using Matlab® for all signal processing procedures, which included signal demodulation and correlation with the 15 emitted code patterns (5 for each U-LPS), peak detection, TDOA computation and position estimation through a Gauss-Newton hyperbolic trilateration algorithm. Fig. 9 summarizes the tasks to be carried out at the receiver.

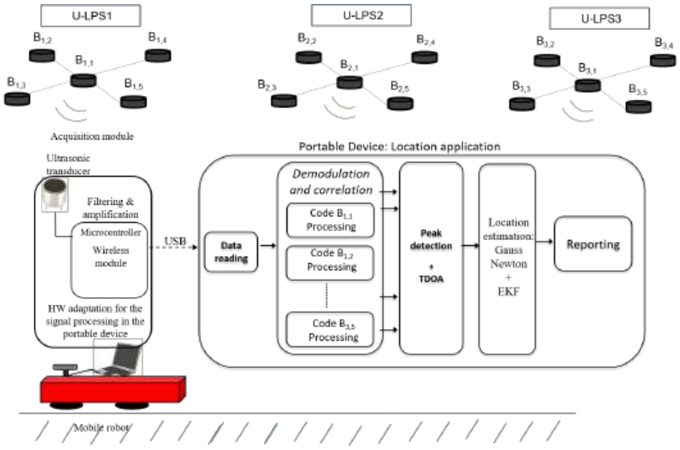


Figure 9: General view of signal processing at the receiver for the LOCATE-US system.

*4.4. ALCOR Team (*out-of-track *section)*

According to a comparison of indoor technologies published in [39], accuracy and coverage performance of infrared, ultrasound, UWB and RFID are typical for indoor systems. The technology used by the ALCOR team was a scanning laser range finder [40], mainly due to its better accuracy. The chosen sensor device was a Hokuyo URG-04LX, with its light source being an infrared laser of $785nm$ (class 1 safety). The angular resolution is $0.36°$, and the distance resolution is $1mm$. Distance accuracy is 3% for detected distances up to 4 m [41]. Every $100ms$, the device scans a sector of $240°$ with a maximum radius of $4m$; consequently, for extended working areas, such as the one in this competition, several units are required.

The methodology to obtain the indoor positioning of a P3-DX robotic unit working in the coverage area of a $\mathrm{URG}-04\mathrm{LX}$ sensor, is described in [40]. Basically, in every sweep the sensor obtains a set of points where the laser impacts on the robot target. From these points, the position of the center of the mobile object is estimated in polar coordinates, having their origin at the laser location, plus some error due to noise and sensor quantification.

As the IPIN Track 4 working area exceeded the coverage of the scanning laser, a network of 4 sensor modules (SMs) was chosen for this application. The key element of each SM is a scanner laser, but it is located on-board a P3-DX robot to ease powering them and registering the generated information. Fig. 10 gives a partial view of the IPIN Track 4 scenario, with 3 SMs and the robot under test. The figure also shows the pattern (the white cylinder) used as the target reference. The black cylinder stands (CP2 and CP3 in Fig. 10) were only used during calibration.

For the calibration process, the white cylinder was located at the reference points within the scanning range of 2 SMs, one of which should be SM0. This strategy makes it possible to transfer every sensor registration to the reference system of SM0. In Fig. 11, the 4 Sensor Modules (SM0 to SM3) cover the full working area. Eight Calibration Points (CP1 to CP8) are required, where CP1, CP2, and CP3 are provided by the track organization as reference points,

Figure 10: Working area covered by sensor modules (SMs), calibration points (CPs) are also included (ALCOR team).

knowing that the mobile unit starts the trajectory at CP1.

The objective of the calibration process was to determine the relationship between the coordinates of each SMi $(x_{Ti}, y_{Ti}, \alpha_{Ti}), (1 \leq i \leq 3)$, and the reference one SM0 $(x_{T0}, y_{T0}, \alpha_{T0})$. Thus, once the local position (x_{Si}, y_{Si}) of one position S is registered by a SM, the global position (x_{S0}, y_{S0}) is obtained by:

$$\begin{bmatrix} x_{s0} \\ y_{s0} \end{bmatrix} = \begin{bmatrix} cos\alpha_{T_i} & -sin\alpha_{T_i} \\ sin\alpha_{T_i} & cos\alpha_{T_i} \end{bmatrix} \cdot \begin{bmatrix} x_{si} \\ y_{si} \end{bmatrix} + \begin{bmatrix} x_{Ti} \\ y_{Ti} \end{bmatrix} \tag{1}$$

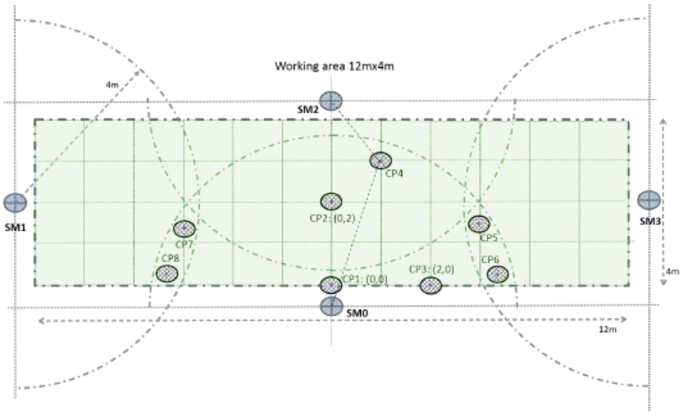


Figure 11: Sensor modules and calibration points involved in the calibration procedure.

4.5. Comparison of the Technologies

In Table 2, we compare the most relevant aspects related to the technology applied by each competitor.

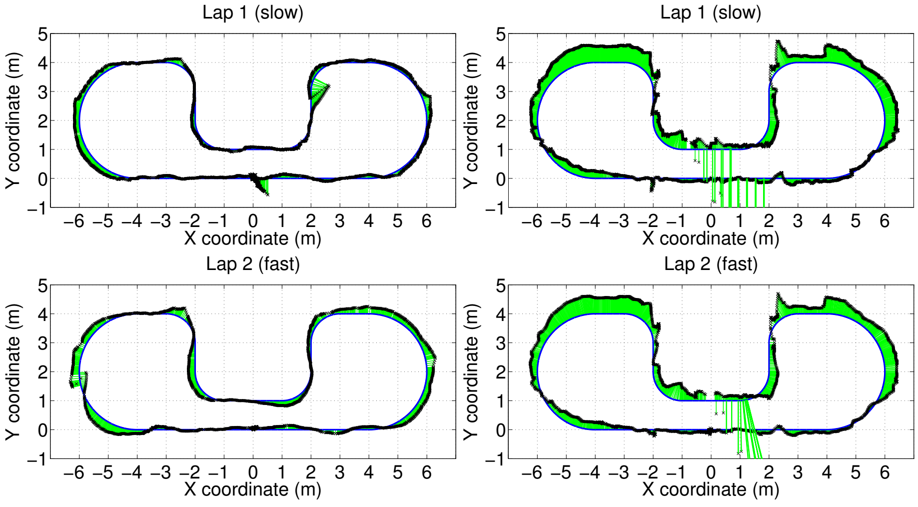
	In-track		Out-of-track	
	ATLAS	TPM	LocateUS	ALCOR
Technology	UWB		Ultrasound	Laser
Method	TOA	TDOA		Phase shift
Hardware modules	Arduino Nano	LPC1347	LPC1768	Hokuyo URG-04LX
	DecaWave DWM1000		Prowave 328ST160	
Sampling frequency	100 Hz	100 Hz	10 Hz	10 Hz
Number of Anchors	At least 3	8 (in pairs of 2)	3 U-LPS, each with 5 transducers	4 SMs
LOS required	No	No	LOS from at least 4 transducers	Yes
Receiver location	On the poles	On the poles	Onboard the robot	Around the working area
Transmitter location	Onboard the robot	Onboard the robot	On the ceiling	

Table 2: Comparison of Technologies.

5. Results and Discussion

Here, we present the results obtained by the in-track and out-of-track competitors. All of them were evaluated with the same robot predefined path and speed, and identical environmental conditions (as described in section 3.2).

Fig. 12 shows the trajectories obtained by the two in-track teams. The real path followed by the robot appears in blue, the participants location estimations are shown as black crosses, and the Euclidean distance to the ground-truth is shown in green. The figures at the top represent the results for the first robot lap, with a speed of up to $0.5m/s$, whereas the figures at the bottom show the results for the second lap, in which the maximum robot speed was $0.8m/s$ on the straight track segments and was lower on the curves. Meanwhile, Fig. 13 depicts the CDF of both participants, what means that 75% of ATLAS measurements present an error lower than $106mm$, being this value $311mm$ for the TPM team.



(a) ATLAS (b) TPM

Figure 12: Track 4 in-track localization error calculation for the estimated robot trajectories in each of the robot laps.

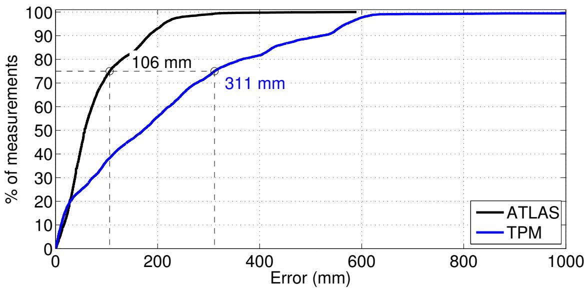
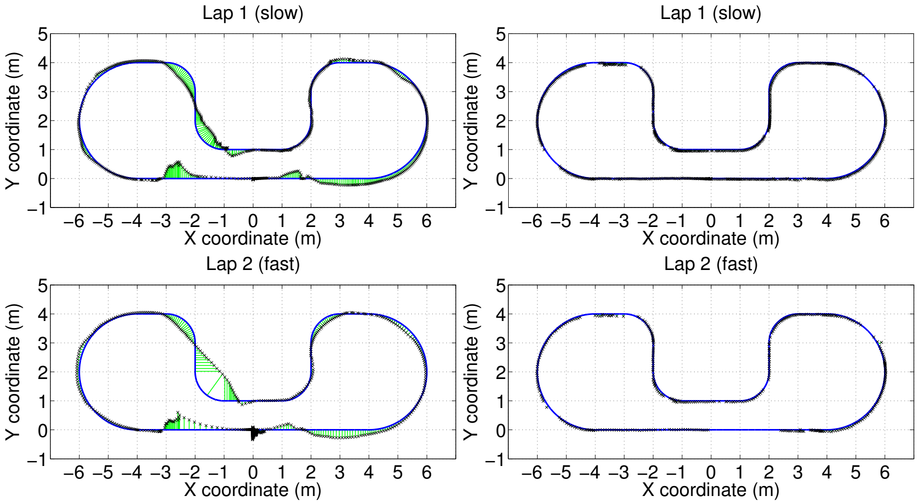


Figure 13: Track 4 CDF results for the ATLAS and TPM systems.

The trajectories followed by the out-of-track competitors are shown in Fig. 14,



(a) LOCATE-US. (b) ALCOR.

Figure 14: Track 4 localization error calculation for the robot trajectories estimated by the out-of-track competitors.

while Fig. 15 gives their CDF results and the third quartile of the error.

Table 3 summarizes the results for Track 4 in terms of average error, standard error deviation, maximum error, and CDF, all of them in millimeters. Note that in indoor robot positioning, the required accuracy and precision of the localization error should usually be higher than that necessary for people navigation applications. Hence, the CDF of the Euclidean distance between the ground-truth positions and the ones estimated by participants is shown not only at 75%, but also at 90% of measurements.

It is worth highlighting that the two out-of-track teams participated as demonstrators, since their deployment and calibration conditions were less strict than those for the competing teams. They could locate their sensors in any position within the competition area (not only on the available poles), and non-limited time was given for deployment and calibration. Apart from their less strict system setup, the other experimental conditions during the robot trajectory were the same as for the in-track teams.

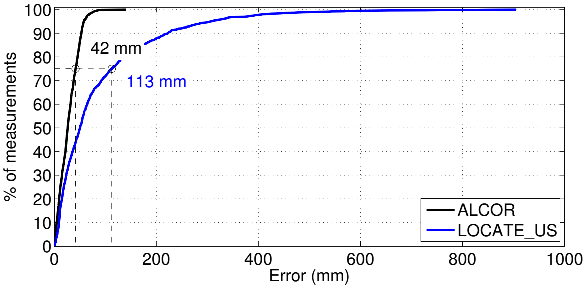


Figure 15: Track 4 CDF results for the LOCATE-US and ALCOR systems.

Team	Mode	Average error	Standard Deviation	Maximum Error	CDF 75%	CDF 90%
ATLAS	In-track	80	68	590	106	183
TPM	In-track	220	271	4659	311	521
LOCATE-US	Out-of-track	87	108	905	113	223
ALCOR	Out-of-track	28	19	140	42	53

Table 3: Results for Track 4 in millimeters.

As is clear from the results shown in Table 3, the ALCOR system based on laser technology obtained better results in terms of accuracy: errors below $5.3cm$ in 90% of cases, with an average error of $2.8cm$ and a standard deviation of mean error in the order of $1.8cm$. Compared with the others, the ALCOR system was highly robust to multipath interference. Note, however, that this system required eight calibration points instead of the three used by the in-track competitors and also line of sight (LOS) between the sensor modules and the mobile unit.

The LOCATE-US ultrasonic system required a more complex deployment than the others, with the beacons installed on the ceiling instead of on the available poles. This distribution minimizes occlusions between the receiver and the ultrasonic emitters. In addition, redundancy was achieved thanks to the five emitters in every U-LPS (only four are necessary for TDOA measurements), which helps to deal with the NLOS measurements.

In the case of the in-track competitors, both of them used UWB technology, so their deployment costs were similar, with 45 minutes setup time. It can be seen that the ATLAS team proposal, based on TDOA, obtained better results than the TPM team, which used TOA instead. Moreover, since the accuracy of TOA and TDOA based localization methods was strongly dependent on beacon topology and the target position, the competition made it possible to evaluate different systems in a challenging scenario with only some fixed positions for the beacons (whose exact coordinates were not known by the competitors), and a mobile target.

Note that the localization errors obtained by Track 4 competitors were in the order of centimeters ($4.2cm$ of the third quartile for the first ranked team, and $31.1cm$ for the last one), which is acceptable for indoor robot positioning in controlled environments [10]. If greater precision is required, the CDF at 90% led to errors below $23cm$ in three of the cases, and of $52cm$ for one of the teams.

Regarding the metrics used, the CDF enabled a comparison of the different systems in terms of third quartile, but it did not take into account other aspects that could be important in real scenarios. Bearing this in mind, future quality metrics should definitely consider the time of deployment and calibration, LOS requirements and cost of the employed sensors.

6. Conclusions and Lessons Learned

The 2016 IPIN robot tracking competition was a successful and challenging experience both for the organizers and the competing teams.

The main difference between this competition and the other tracks in the IPIN competition initiative, and also with respect to other related robot positioning competitions was that accurate tracking of the robot trajectory was required. In addition, the 2016 IPIN robot tracking competition allowed the competitors to deploy specific equipment both off-board and on-board the robot, and they were allowed to carry out calibration procedures within a given time slot.

These two differences had a significant impact on the competition requirements and planning restrictions. First, the competition setup was significantly more challenging, as it had to provide sufficient space for an industrial robot to perform a reasonably complex and varied trajectory. Furthermore, physical elements had to be provided so that the participants could deploy their systems (poles in our case). This implied stating additional considerations in the competition rules, which had to provide sufficiently precise descriptions of the restrictions imposed on the competing teams (maximum sizes, weights, etc.).

Future work will focus on how to handle larger navigation areas while maintaining installation and calibration complexity within reasonable limits.

With respect to the evaluation metrics to be used, accurate calculation of Euclidean-based error metrics also requires accurate estimation of the ground-truth trajectory followed by the robot. This implies having precise time and location information, but these restrictions can be partially alleviated by geometrically defining the robot trajectory, while the accurate timing restriction can be relaxed by using ad-hoc Euclidean distance calculation, as proposed in this paper.

We also found that the set up time for the teams (equipment deployment and calibration, related to installation complexity) imposed a substantial restriction on the systems performance, and this should be considered in the evaluation criteria for future competitions (in line with the proposals to integrate soft metrics in the EvAAL competitions [9, 21]).

Related to the suitability of technological solutions for the task, the competition imposed no restrictions (apart from those related to safety issues and the physical ones required by the sensor equipment to deploy); however, the participants faced the added challenge of a real-time restriction, as the results had to be provided immediately after each run.

For future competitions, establishing different ranks depending on the technology would also help to increase the participation, as some teams might be reluctant to participate if there were a clearly superior technology that would be difficult to beat. In this respect, adding evaluation metrics that also consider technology cost, deployment time, etc. is essential to encourage wider participation. Regarding the evaluation scenario, larger evaluation areas (or paths) should be considered, as well as the inclusion of some obstacles (to the RF/acoustic signals or to line of sight, depending on the deployed sensors). The use of alternative robotic platforms could also be evaluated (probably including 3D scenarios accounting for variations in pitch and roll).

The results presented here provide a good baseline for assessing the capability of the technologies employed to face similar tasks, and are very well within state-of-the-art performance (minimum average errors below $3cm$, and CDF errors at 75% around $4cm$).

Acknowledgments

Parts of this job were funded by the Spanish Ministry of Economy and Competitiveness under projects SPACES-UAH (TIN2013-47630-C2-1-R), HEIMDAL (TIN2016-75982-C2-1-R), TARSIUS (TIN2015-71564-c4-1-R) and ALCOR (DPI 2013-47347-C2-1-R), by the REDPIN national network TEC2015-71426-REDT and by the University of Alcalá under projects ESCALA (CCG2016/EXP-010), DETECTOR (CCG2015/EXP-019), ARMIS (CCG2015/EXP-054) and ECHO-DRONE3D (CCGP2017/EXP-050). Parts of this job were partially funded by Deutsche Forschungsgemeinschaft (DFG) within the Collaborative Research Center SFB 876 “Providing Information by Resource-Constrained Analysis”, project A4 and was supported by the federal state of Northrhine-Westphalia and the “European Regional Development Fund” (EFRE) 2014-2020.

Conflicts of interest: none.

References

[1] H. Kitano, M. Asada, Y. Kuniyoshi, I. Noda, E. Osawa, RoboCup: The Robot World Cup Initiative, in: Proceedings of the First International Conference on Autonomous Agents, AGENTS ’97, ACM, New York, NY, USA, 1997, pp. 340–347. doi:10.1145/267658.267738.

[2] D. M. Budden, P. Wang, O. Obst, M. Prokopenko, Robocup simulation leagues: Enabling replicable and robust investigation of complex robotic systems, IEEE Robotics and Automation Magazine 22 (3) (2015) 140–146.

[3] J. Martínez-Gómez, B. Caputo, M. Cazorla, H. I. Christensen, M. Fornori, I. García-Varea, A. Pronobis, Where are we after five editions?: Robot vision challenge, a competition that evaluates solutions for the visual place classification problem, IEEE Robotics and Automation Magazine 22 (4) (2015) 147–156. `doi:10.1109/MRA.2015.2460931`.

[4] A. Jacoff, E. Messina, B. A. Weiss, S. Tadokoro, Y. Nakagawa, Test arenas and performance metrics for urban search and rescue robots, in: Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on, Vol. 4, 2003, pp. 3396–3403 vol.3. `doi:10.1109/IROS.2003.1249681`.

[5] H. A. Yanco, J. L. Drury, Rescuing interfaces: A multi-year study of human-robot interaction at the aaai robot rescue competition, Autonomous Robots 22 (4) (2007) 333–352. `doi:10.1007/s10514-006-9016-5`.

[6] AUVSI SUAS competition, `http://www.auvsi-suas.org/competitions/2016/`, [Last accessed September 2018] (2016).

[7] T. Braunl, et al., Research relevance of mobile robot competitions, IEEE Robotics and Automation Magazine 6 (4) (1999) 32–37.

[8] M. Anderson, O. C. Jenkins, S. Osentoski, Recasting robotics challenges as experiments, IEEE Robotics and Automation Magazine 18 (2) (2011) 10–11. `doi:10.1109/MRA.2011.941627`.

[9] P. Barsocchi, S. Chessa, F. Furfari, F. Potortì, Evaluating AAL solutions through competitive benchmarking: the localization competition, IEEE Pervasive Computing Magazine 12 (4) (2013) 72–79. `doi:10.1109/MPRV.2013.23`.

[10] Microsoft indoor localization competition, `https://goo.gl/ZwU8mS`, [Last accessed September 2018] (2014).

[11] N. Hernández, M. Ocaña, J. M. Alonso, E. Kim, Continuous space estimation: Increasing wifi-based indoor localization resolution without increasing the site-survey effort, Sensors 17 (1). `doi:10.3390/s17010147`.

[12] J. Shang, X. Hu, W. Cheng, H. Fan, Gridiloc: A backtracking grid filter for fusing the grid model with pdr using smartphone sensors, Sensors 16 (12). `doi:10.3390/s16122137`.

[13] Z. Tian, Y. Jin, M. Zhou, Z. Wu, Z. Li, Wi-fi/marg integration for indoor pedestrian localization, Sensors 16 (12). `doi:10.3390/s16122100`.

[14] L. Pérez, I. Rodríguez, N. Rodríguez, R. Usamentiaga, D. F. García, Robot guidance using machine vision techniques in industrial environments: A comparative review, Sensors 16 (3). `doi:10.3390/s16030335`.

[15] T. Seco, C. Rizzo, J. Espelosn, J. L. Villarroel, A robot localization system based on rf fadings using particle filters inside pipes, in: 2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2016, pp. 28–34. `doi:10.1109/ICARSC.2016.22`.

[16] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, V. Handziski, S. Sen, A realistic evaluation and comparison of indoor location technologies: Experiences and lessons learned, in: Proceedings of the 14th international conference on information processing in sensor networks, ACM, 2015, pp. 178–189. `doi:10.1145/2737095.2737726`.

[17] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, S. Sen, V. Handziski, Microsoft indoor localization competition: Experiences and lessons learned, GetMobile: Mobile Computing and Communications 18 (4) (2015) 24–31. `doi:10.1109/MSP.2017.2713817`.

[18] F. Potortì, P. Barsocchi, M. Girolami, J. Torres-Sospedra, R. Montoliu, Evaluating indoor localization solutions in large environments through com-

petitive benchmarking: The EvAAL-ETRI competition, in: Indoor Positioning and Indoor Navigation (IPIN), 2015 International Conference on, 2015, pp. 1–10. doi:10.1109/IPIN.2015.7346970.

[19] T. Van Haute, E. De Poorter, J. Rossey, I. Moerman, V. Handziski, A. Behboodi, F. Lemic, A. Wolisz, N. Wiström, T. Voigt, et al., The EVARILOS benchmarking handbook: Evaluation of RF-based indoor localization solutions, in: 2e International Workshop on Measurement-based Experimental Research, Methodology and Tools (MERMAT 2013), 2013, pp. 1–6. doi:10.13140/2.1.2218.4325.

[20] T. Van Haute, E. De Poorter, F. Lemic, V. Handziski, N. Wirström, T. Voigt, A. Wolisz, I. Moerman, Platform for benchmarking of RF-based indoor localization solutions, IEEE Communications Magazine 53 (9) (2015) 126–133. doi:10.1109/MCOM.2015.7263356.

[21] F. Lemic, V. Handziski, A. Wolisz, T. Contambeys, C. Laoudias, S. Adler, S. Schmitt, Y. Yang, Experimental evaluation of rf-based indoor localization algorithms under rf interference, in: 2015 Inernational Conference on Localization and GNSS (ICL-GNSS), 2015, pp. 1–8. doi:10.1109/ICL-GNSS.2015.7217149.

[22] D. Salvi, P. Barsocchi, M. T. Arredondo, J. P. L. Ramos, EvAAL, evaluating AAL systems through competitive benchmarking, the experience of the 1st competition, in: International Competition on Evaluating AAL Systems through Competitive Benchmarking, Springer, 2011, pp. 14–25. doi:10.1007/978-3-642-33533-4.

[23] P. Barsocchi, S. Chessa, F. Furfari, F. Potort, Evaluating ambient assisted living solutions: The localization competition, IEEE Pervasive Computing 12 (4) (2013) 72–79.

[24] F. Potorti, S. Park, A. R. Jimnez, P. Barsocchi, M. Girolami, A. Crivello, S. Y. Lee, J. H. Lim, J. Torres-Sospedra, F. S. ans R. Montoliu ans

G. M. Mendoza-Silva, M. C. Pérez-Rubio, C. Losada-Gutiérrez, F. Espinosa, J. Macias-Guarasa, Comparing the performance of indoor localization systems through the evaal framework, Sensors 17 (10) (2073) 1–28.

[25] J. A. Álvarez-García, P. Barsocchi, S. Chessa, D. Salvi, Evaluation of localization and activity recognition systems for ambient assisted living: The experience of the 2012 EvAAL competition, Journal of Ambient Intelligence and Smart Environments 5 (1) (2013) 119–132. `doi:10.3233/AIS-120192`.

[26] ASTi automated conveyance web, `http://asti.es/en/soluciones/transporte-automatico`, [Last accessed September 2018] (2016).

[27] 360 photosphere picture of the location of the ipin 2016 track 4 competition, `https://goo.gl/ibEqUn` [Last accessed September 2018] (september 2018).

[28] M. C. P. Rubio, C. Losada-Gutiérrez, F. Espinosa, J. Macias-Guarasa, Track 4: Indoor Mobile Robot Positioning Competition Rules, `http://www.geintra-uah.org/archivos/Track4_format_FAQ.pdf` [Last accessed September 2018] (september 2018).

[29] M. C. P. Rubio, C. Losada-Gutiérrez, F. Espinosa, J. Macias-Guarasa, Track 4: Practical Issues of the Indoor Mobile Robot Positioning Competition, `http://www.geintra-uah.org/archivos/Track4_practical_issues_v1.pdf` [Last accessed September 2018] (september 2018).

[30] J. Tiemann, F. Eckermann, C. Wietfeld, Multi-user interference and wireless clock syncronization in tdoa-based uwb localization, in: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcalá de Henares, Madrid, Spain, 2016, pp. 1–6. `doi:10.1109/IPIN.2016.7743696`.

[31] DecaWave Ltd., DWM1000 IEEE 802.15.4-2011 UWB Transceiver Module Datasheet 1.0 (2014).

[32] J. Tiemann, ATLAS UWB node hardware design, http://dx.doi.org/10.5281/zenodo.61464 (Sep 2016). doi:10.5281/zenodo.61464.

[33] J. Tiemann, ATLAS localization server source code, http://dx.doi.org/10.5281/zenodo.61465 (Sep 2016). doi:10.5281/zenodo.61465.

[34] J. Tiemann, F. Eckermann, C. Wietfeld, ATLAS - an Open-Source TDOA-based Ultra-Wideband Localization System, in: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcalá de Henares, Madrid, Spain, 2016, pp. 1–6. doi:10.1109/IPIN.2016.7743707.

[35] Pro−Wave Electronics Corporation, Air Ultrasonic Ceramics Transducers 328ST/R160, Product specification (2014).

[36] NXP Semiconductors, LPC1768 Product Data Sheet (2014).

[37] Knowles Acoustics, SPU0414hR5H-SB Amplified SiSonic^{TM} Microphone product data sheet (2013).

[38] M. C. Pérez, D. Gualda, J. M. Villadangos, J. U. na, P. Pajuelo, E. Díaz, E. García, Android application for indoor positioning of mobile devices using ultrasonic signals, in: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcalá de Henares, Madrid, Spain, 2016, pp. 1–7. doi:10.1109/IPIN.2016.7743613.

[39] R. Mautz, Indoor positioning technologies, Ph.D. dissertation (Feb 2012). doi:doi.org/10.3929/ethz-a-007313554.

[40] M. M. Rey, E. Santiso, F. Espinosa, R. Nieto, A. Gardel, Smart laser scanner for event-based state estimation applied to indoor positioning, in: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcalá de Henares, Madrid, Spain, 2016, pp. 1–7. doi:10.1109/IPIN.2016.7743613.

[41] Hokuyo Automatic Co. Ltd., URG−04LX User Manual - Scanning Laser Range Finder Specifications (2005).