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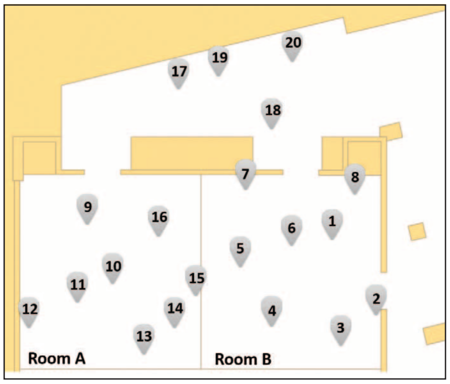
MICROSOFT INDOOR LOCALIZATION COMPETITION:
EXPERIENCES AND LESSONS LEARNED

For well over a decade, academia and industry have devoted a lot of effort and resources into solving the indoor localization problem. The research community has not converged to a single, widely accepted solution that can achieve the desired accuracy at the required cost. We believe that this is partly due to the highly ad-hoc evaluation process of indoor location systems: each system is usually evaluated in a custom, highly controlled environment, making it hard to draw conclusions about its performance and overhead in realistic conditions. Even worse, this type of evaluation makes the comparison of different solutions almost impossible.

With this in mind, we organized the Microsoft Indoor Localization Competition [1]. The main motivation behind the competition was to give different academic and industry groups the opportunity to test their indoor location technologies in a realistic, unfamiliar environment. This environment established a common baseline for assessing the relative accuracy and overhead of the different indoor location technologies. At the same time, it allowed researchers working on the indoor location to meet and interact with each other, and closely observe the competing solutions in action.



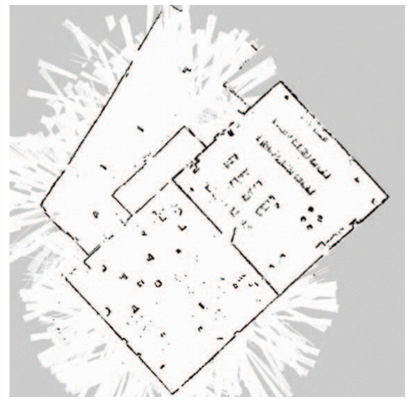
(a) The 20 test points on the evaluation area

(b) Room A

(c) Room B

(d) Recording system under test's location

(e) EVARILOS robot



(f) Automatically mapped floorplan

FIGURE 1. The 300m2 area used for the competition. 20 evaluation points were placed into two rooms and the hallway. Besides the manual evaluation, the EVARILOS robot automatically mapped the competition area and then was used to automatically evaluate the accuracy of the top two teams.

COMPETITION

Participating Teams

21 teams with 22 different approaches attended the competition (Table 1). All teams were classified into two categories: *infrastructure-free* and *infrastructure-based*, based on their hardware deployment requirements. Teams in the *infrastructure-free* category did not require the deployment of any custom hardware, apart from existing WiFi infrastructure, to compute indoor locations. Most of these approaches leveraged existing WiFi signals and combined them with sensors, such as an accelerometer, gyro, and compass, on existing off-the-shelf devices such as phones and tablets. On the other hand, teams in the *infrastructure-based* category required the deployment of custom hardware, such as bluetooth beacons, magnetic resonators, ultrasound speakers, and custom RF transmitters.

Overall, 9 teams competed in the *infrastructure-free* category, and 13 teams competed in the *infrastructure-based* category (Table 1).

Setup and Evaluation

The competition took place in Berlin, Germany at the hotel venue of the 2014 International Conference on Information Processing in Sensor Networks (IPSN). Two attached rooms, each measuring 10*m* by 9*m* in dimensions, and the hallway in front of the two rooms (measuring approximately 10*m* by 4*m*) were used for the competition. *Figure 1* shows the floor plan of the approximately 300m^2 evaluation area .

The competition was a 2-day event. During the first day, all competitors were given 7 hours to set up their indoor location technologies in the evaluation area. During this time, teams were able to deploy their custom hardware, if any, and also perform any profiling of the space necessary (i.e., fingerprinting, map construction etc.). Each team was allowed to deploy up to 10 infrastructure points (i.e., access points, custom RF modules, magnetic field modulators, light-modulating lamps, etc.) in the evaluation area.

To avoid having each team deploying their own generic WiFi access points, the competition organizers deployed 10 WiFi access points in the evaluation area. Each room was equipped with 5 access points, one at each corner of the room and one in the middle of the room. The deployed access points were mounted on cocktail tables like the ones shown in *Figure 1*(b) at a height of approximately 1.5*m* from the ground. All the teams that relied on generic WiFi access points for estimating indoor location could only use these access points.

At the beginning of the first day, the organizers indicated an origin point for the reference coordinate system that each team should use to report locations. Locations were reported as two-dimensional coordinates (i.e., (2.12*m*, 5.1*m*)) with respect to the origin point.

At the end of the first day, the deployed hardware from all teams was turned off, and all contestants left the evaluation area. At that time, the organizers marked 20 points on the floor of the evaluation area and measured the X and Y coordinates of these points with respect to the predefined origin point (*Figure 1*(a)). The ground truth measurements of the evaluation points were taken using laser range finders, leading to centimeter-level accuracy.

During the second day of the competition, each team showed up at a pre-assigned time slot, turned on its deployed hardware, and handed the device to be localized to the organizers. The organizers carried the device above each of the 20 evaluation points and recorded the locations reported by the system under test. All systems were evaluated based on the average location error across all 20 evaluation points. The location error for a given point was defined as the Euclidean distance between the true and reported coordinates for that point.

To assess the ability of each approach to localize devices at dynamic/unfamiliar environments, part of the evaluation area's furniture placement was modified after the setup day and before the evaluation day. More specifically, both rooms in *Figure 1*(a) were equipped with furniture. Approximately half of each room was filled with tables and chairs resembling a typical classroom setup. The other half of the rooms were either empty or sparsely occupied by tall cocktail tables (*Figure 1*(a) and *Figure 1*(b)). Room A, shown in *Figure 1*(a), remained unchanged between the setup

TABLE 1: The teams that participated in the Microsoft Indoor Localization Competition

	Team	Team's Affiliation	Country	Technical Approach	Global Rank
INFRASTRUCTURE-BASED	Bestmann et al. [19]	Lamda:4	Germany	2.4GHz Phase Oset	1
	Li et al. [14]	Microsoft Research	China	Modulated LEDs	4
	Adler et al. [3]	Freie Universitat Berlin	Germany	2.4GHz Time-of-Flight	5
	Lazik et al. [11]	Carnegie Mellon University	USA	Ultrasonic Time-of-Flight	6
	Ashok et al. [4]	Rutgers University	USA	IR/Radio Time-of-Flight	8
	Nikodem et al. [17]	Wroclaw University of Technology	Poland	2.4GHz Time-of-Flight	9
	Dentamaro et al. [6]	NextoMe	Italy	WiFi+Bluetooth+IMU	10
	Abrudan et al. [2]	University of Oxford	U.K.	Modulated Magnetic Signals	15
	Sark et al. [20]	Humboldt University of Berlin	Germany	SDR Time-of-Flight	16
	Pirkl et al. [18]	DFKI	Germany	Modulated Magnetic Signals	17
	Schmid et al. [21]	Greina Technologies	USA	2.4GHz Phase Oset	18
	Jiang et al. [10]	Xian Jiaotong University,	China	WiFi+Sound Time-of-Flight	1
	Selavo et al. [22]	I.E.C.S.	Latvia	Steerable Antennas ToF	22
INFRASTRUCTURE-FREE	Klepal et al. [5]	Cork Institute of Technology	Ireland	WiFi Fingerprinting	2
	Laoudias et al. [13]	University of Cyprus	Cyprus	WiFi+IMU Fingerprinting	3
	Zou et al. [25]	Nanyang Technological University	Singapore	WiFi Fingerprinting	7
	Ferraz et al. [7]	Ubee S.A.	Brazil	WiFi+IMU Fingerprinting	11
	Li et al. [15]	Microsoft Research	China	WiFi+IMU Fingerprinting	12
	Marcaletti et al. [16]	ETH/IMDEA/Armasuisse	Switzerland/Spain	WiFi Time-of-Flight	13
	Xiao et al. [23]	University of Oxford	U.K.	WiFi+IMU+Maps	14
	Zhang et al. [24]	Nanyang Technological University	Singapore	WiFi+Magnetic Fingerprinting	19
	Ghose et al. [8	Tata Consulting Services	India	WiFi+IMU Fingerprinting	20

TABLE 1. The teams that participated in the Microsoft Indoor Localization Competition. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest). Adler et al., and Li et al. achieved almost identical location errors (0.005m dierence), and we considered this to be a tie. The second place was awarded to Li et al., because they deployed fewer anchor nodes.

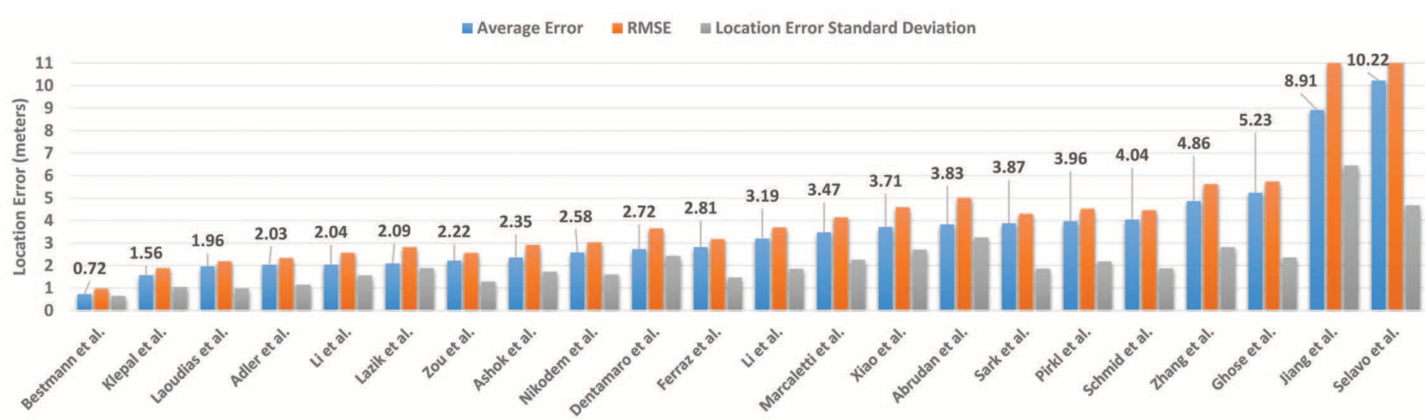


FIGURE 2. Average location error, root mean square error(RMSE), and the standard deviation of the location error for all 22 competing approaches. As a reference, if a team were to always report the center of the evaluation area as the true location, the average location error would be 7 meters.

and evaluation days. The furniture in Room B (*Figure 1*(b)) were completely rearranged in terms of both placement and orientation. Competitors were not aware of which room will be modified and how until the evaluation day. This allowed us to evaluate the accuracy of the different approaches in both familiar and unfamiliar setups.

Two more sources of unfamiliarity were also introduced during the competition. First, even with the organizers deploying the WiFi access points, there was still a huge level of wireless interference during the first day of the competition when all teams were simultaneously profiling the space and calibrating their systems. The wireless interference was significantly reduced during the second day of the competition when evaluation took place, as only one system was active at a time. Second, during both days of the event (setup and evaluation days), people attending the competition as well as people attending the IPSN conference were more than welcome to enter the rooms and walk around. This provided varying levels of occupancy and human movement in the evaluation area.

Automatic Evaluation

Even though the official evaluation was based on the manual process described in the previous section, the organizers had the ability to leverage the EVARILOS benchmarking platform [9] to automatically evaluate the localization accuracy of the two wining solutions in the *infrastructure-based* and *infrastructure-free* categories.

The EVARILOS benchmarking platform is an integrated experimental infrastructure that fully automates the evaluation of indoor localization systems [12]. It leverages the TWISTbot mobility platform (*Figure 1*(e)) comprised of a Kubuki mobility base, a Microsoft Kinect sensor and a Hokuyo URG-04L laser ranger, to enable accurate and repeatable positioning of the evaluated localization devices at different evaluation points.

During the competition, the TWISTbot platform was able to automatically extract the floor plan of the evaluation area using its onboard sensors (*Figure 1*(f)). Each team's device was mounted on top of the robot, and then the robot was given the true coordinates of each of the 20 evaluation points. In response, the robot autonomously navigated to the evaluation points and when there, it recorded the location of the system under test. Even though, the EVARILOS benchmarking platform can interact with the evaluated localization system over a well-defined API, locations were manually recorded and compared with the ground-truth information provided by the TWISTbot to reduce the integration overhead for the competitors.

RESULTS

Figure 2 shows the localization accuracy of all 22 competing approaches. The average location error achieved varied between 0.72*m* and 10.22*m*. Only 3 teams were able to achieve less than 2*m* accuracy, while half of the teams achieved less than 3*m* error.

The clear winner of the competition was the EasyPoint system by Bestman et al. [19] with an average location error of 0.72*m*. It is worth noting that Bestmann et al. opted to deploy only 6 out of the total 10 anchor nodes they were allowed to deploy.

In the *infrastructure-based* category, Bestman et al. was followed by Li et. al [14] (only 5 LED lamps were deployed), Adler et al. [3], and Lazik et al. [11], with all 3 teams achieving almost identical location errors (2*m* - 2.1*m*).

In the *infrastructure-free* category, the MapUme submission by Klepal et al. [5] achieved the lowest location error (1.6m). Submissions by Laoudias et al. [13], Zou et al. [25], and Ferraz et al. [7] followed with location errors of 1.96*m*, 2.22*m*, and 2.81*m*, respectively.

Overall, even though different teams leveraged similar techniques for indoor location estimation, the variance across implementations was significant. For instance, the accuracy achieved by approaches measuring time-of-flight or phase offset in the 2.4GHz range varied from 0.72*m* (Bestmann et al.) all the way to approximately 4*m* (Schmid et al.). Similarly, WiFi-only approaches exhibited similar variations ranging from 1.6*m* (Klepal et al.) to approximately 5*m* (Ghose et al.) location accuracy. On the other hand, the two teams that leveraged modulated magnetic signals (Abrudan et al., and Pirkl et al.) achieved similar accuracy (approximately 4*m*).

Figure 3 shows the empirical CDF of the location errors for the top 4 teams in both categories. The top approaches in both categories (Bestmann et al., and Klepal et al.) are clearly ahead of the other teams. Surprisingly, the performance of the remaining top approaches is very similar independently of any custom infrastructure used. The difference between *infrastructure-based* and *infrastructure-free* approaches is rather small (approximately 0.5*m*). Also, the maximum location errors produced by *infrastructure-based* approaches can be higher than that of *infrastructure-free* approaches.

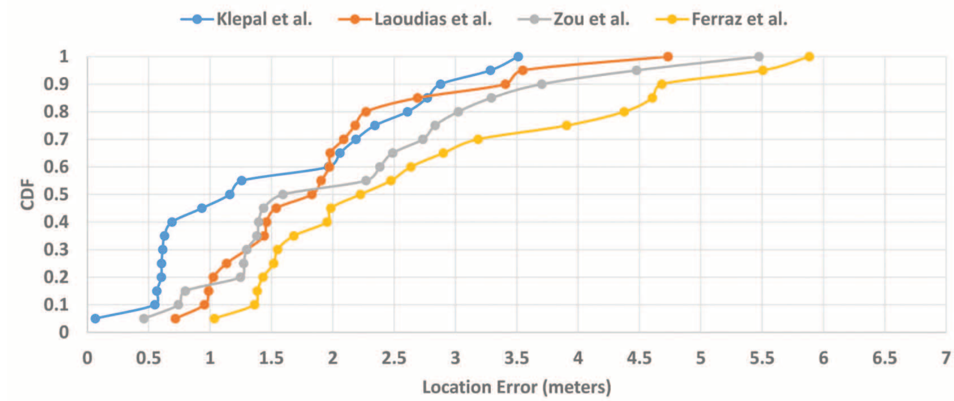
The Impact of Furniture Setup

Right after the setup day and before the evaluation day, the furniture setup in Room B was modified, while the furniture setup in Room A remained the same (*Figure 1*). Table 2 shows the average location error achieved by the top 4 teams in both categories and for each of the two rooms separately. With the exception of Laoudias et al., the rest of the *infrastructure-free* approaches report higher location errors in the room where the furniture setup was modified. The error increase varies anywhere between 0.47*m* and 0.94*m*.

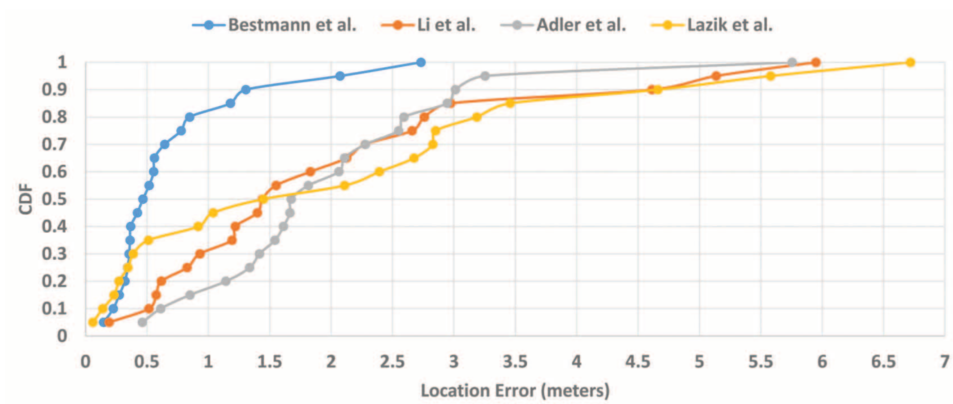
Surprisingly, even *infrastructure-based* approaches seem to be affected by the changes in the furniture setup. The top 4 teams in this category, with the exception of Adler et al., exhibited increase in location errors in the modified room that varied anywhere between 0.11*m* and 2.99*m*. For Bestmann et al., and Adler et al. the error difference between the rooms is rather small, but for the rest of the approaches the error increase can be even higher than that of *infrastructure-free* approaches. We believe that this is primarily due to differences in the way these teams deployed hardware in the two rooms, and not due to the furniture setup in the rooms. For instance, Li et al. deployed only 2 LED lamps in the modified room and 3 LED lamps in the room that remained identical. This type of deployment decisions are the main source of error increase in the case of *infrastructure-based* approaches in Table 2.

Variance Across Evaluation Points

Figure 4 shows the average location error across all teams for each of the 20 evaluation points. At a high-level, there seem to be good and bad points in terms of location



(a) Top 4 infrastructure-free approaches



(b) Top 4 infrastructure-based approaches

FIGURE 3. Empirical cumulative distribution function of the location error for the top 4 teams in the infrastructure-free and infrastructure-based categories.

TABLE 2: Average Location Error (meters)

Approach	Identical Room	Modified Room
Infrastructure-free		
Klepal et al.	1.2	1.67
Laoudias et al.	2.21	1.92
Zou et al.	1.75	2.69
Ferraz et al.	2.09	2.91
Infrastructure-based		
Bestmann et al.	0.6	0.71
Li et al.	1.15	2.06
Adler et al.	2.16	1.95
Lazik et al.	0.71	3.7

TABLE 2. Average location error achieved by the top 4 approaches in each category for the two rooms. Most of the approaches experienced signicant increase in location error in the room where the furniture location and orientation was modied.

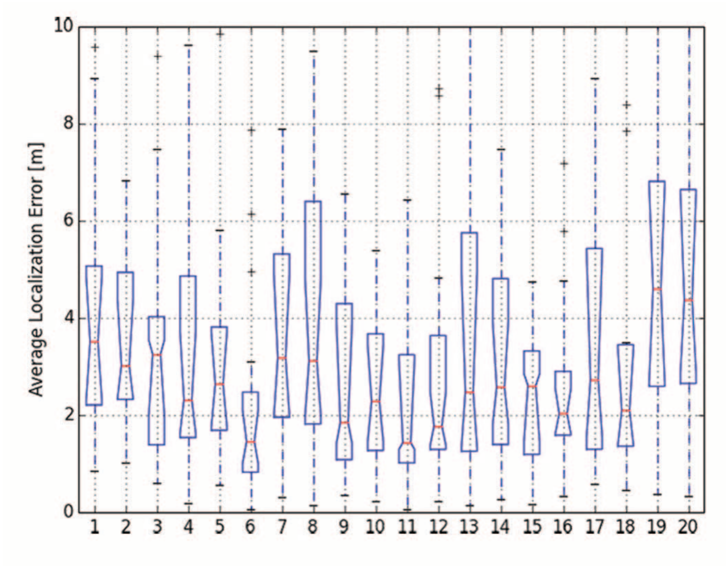


FIGURE 4. Average location error and its standard deviation across all teams for each of the 20 evaluation points.

TABLE 2: Average Location Error (meters)

Approach	Manual	Robot
Bestmann et al.	0.72	0.72
Klepal et al.	1.56	1.71

TABLE 3. Automatic evaluation using the EVARILOS benchmarking platform. For Klepal et al., the robot evaluation included only 18 out of the total 20 evaluation points. Obstacles or failures in robot's navigation, prevented the robot from placing the system-under-test above the remaining two evaluation points.

accuracy. For instance, points 6, 9, 10, 11, 12, and 16 tend to generate lower location errors compared to the rest of the evaluation points. It is interesting to note that all these points tend to be located towards the center of the two evaluation rooms. On the other hand, points located at the edges of the rooms (i.e., 1, 2, 7, 8), or at the hallway (i.e., 19, 20) generate the highest location error with the largest deviations.

Robot-based Evaluation

The best two teams in the competition (Bestmann et al., and Klepal et al.), as determined by the manual evaluation process, were invited to another evaluation round using the EVARILOS benchmarking platform described in Section 2.2.1..

Table 3 shows the average location error for both the robot and the manual evaluation process. Surprisingly, the approach by Bestmann et al. was able to achieve the exact same localization accuracy indicating the stability and reliability of the technology. The accuracy of the approach by Klepal et al. was only slightly increased by 0.15*m*. Given that this is a pure WiFi-based approach, the overall accuracy and its stability is impressive.

The results in Table 3 also show the feasibility of automating the evaluation process of indoor location technologies using properly equipped robots. Even though the evaluation area was a very challenging navigation and locomotion environment due to the presence of lot of people and installed localization infrastructure (including a lot of loose cabling on the floors), the TWISTbot mobility platform was able to position the system-under-test devices to the different evaluation points with acceptable precision and reliability. With an average positioning error of less than 25*cm*, the results confirm that the quality of the TWISTbot navigation, even under such challenging conditions, is sufficiently high so that the robot can be indeed used as a source of ground-truth information for automatic evaluation of many indoor localization solutions that typically have location estimate errors that are several multiples of this value.

LESSONS LEARNED

This competition allowed us to closely observe and evaluate multiple teams deploying various technologies in an unfamiliar area. Even though the competing teams did not cover every single research and industry effort in the indoor location space, we believe that the submissions are representative of the most popular indoor location technologies. Therefore, based on the analysis of the results and our experience organizing this event, we believe we can safely extract a set of high level conclusions.

The Indoor Location Problem is NOT Solved

After more than a decade of intensive work in this area, the indoor location problem remains unsolved. There does not seem to exist a technology or a combination of technologies that can recreate the experience that GPS offers outdoors in the indoor environment. Even though Klepal et al. managed to achieve an impressive 1.6*m* accuracy solely based on off-the-shelf access points, and Bestmann et al. were able to achieve 0.72*m* location error, this level of accuracy can only enable a subset of the envisioned indoor localization scenarios. Applications that require room-level or even meter level accuracy (i.e., indoor navigation), can be easily powered by such technologies.

However, more sophisticated applications such as dynamic personalized pricing, and product placement and advertisements in the context of retail stores (i.e., grocery or clothing stores) require much higher granularity of location information. In such scenarios, there might be tens of different products within a meter distance from the user, rendering the current systems inefficient.

Deployment Overhead Remains Too High

Most of the teams that participated in the competition had to deploy custom infrastructure, and the rest had to manually profile the evaluation area. From directly observing all the teams during the setup day of the competition, it became clear that the deployment/profiling cost of current approaches is prohibitively high. All teams were given 7 hours to deploy their hardware and/or profile a relatively small area of $300m^2$. Even though one would think that 7 hours should be way more than enough time for the teams to setup their systems, this wasn't the case. Most teams (with a couple of exceptions) required all 7 hours to set up, and for some teams 7 hours was not enough to profile the whole $300m^2$ of the competition space. This is particularly concerning given the fact that the teams did not have to worry about any practical issues that any commercial deployment would impose (i.e., aesthetics, properly hiding the deployed equipment, etc.).

In addition, the whole process of deploying custom hardware and profiling the space was quite intrusive. We don't believe that any business owner would like to perform either of these two tasks while real customers are in the business.

When considering the massive size of deployment candidate sites (i.e., shopping malls) and how intrusive, time consuming and labor intensive the processes of deploying hardware and profiling the space are, realistic indoor location deployments that can achieve centimeter-level accuracy seem infeasible at this point. Reducing the overhead and manual labor required by the different indoor location technologies is of paramount importance for their success.

Custom Hardware Solutions Are Not Mature Enough

Most of the competing teams employed customized hardware in their systems. However, only Bestmann et al. was able to achieve better accuracy than the top two *infrastructure-free* approaches (Klepal et al., Laoudias et al). Even though solely based on commercially available access points and sensors, these two approaches were able to achieve less than 2 meters location error, performing significantly better than most *infrastructure-based* approaches. Even worse, the winning system by Bestmann et al., achieved a location error of 0.72*m*, which is only half of the *infrastructure-free* approaches' error.

Given that *infrastructure-based* solutions require orders of magnitude higher deployment cost (i.e., more time consuming, higher financial cost, more intrusive etc.) compared to *infrastructure-free* approaches, the improvement they currently offer in terms of localization accuracy does not justify their existence. We believe that *infrastructure-based* approaches are promising, but nowhere close to where they should be. To become an interesting alternative, any approach in this area needs to achieve significantly higher localization accuracy than traditional WiFi-based indoor location techniques.

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Changes in the Environment Impact Accuracy

Even though previous studies have already shown that large objects such as furniture and human presence can impact localization accuracy, indoor location technologies are typically evaluated on static environments. By modifying the furniture setup in one of the rooms in the evaluation area we were able to quantify the impact of large objects on different indoor location approaches. *Infrastructure-free* approaches that rely on WiFi signals can experience up to 1 meter of location error increase due to furniture setup changes (Table 2). This is particularly high considering that the average location error of the top *infrastructure-free* approach was 1.6*m*. However, the increase in location error depends heavily on the implementation. For instance, the top two teams in the *infrastructure-free* category experience less than 0.5*m* or even no increase in error at all when the furniture setup is altered.

Redesigning Indoor Location Evaluation

The way indoor location technologies are evaluated and compared can be rather tricky. Even though various metrics have been proposed in the literature (i.e., average location error, RMSE, 95th percentile etc.), there are variations in the real world that are not being properly captured by these metrics. For instance, as *Figure 4* shows, not all evaluation points are equal. There are easy points that almost any indoor location approach can easily handle, and there are points that are really hard to accurately localize. As a result, the way evaluation points are selected and weighted in the evaluation metric becomes crucial. We believe that a lot of work needs to be done in terms of standardizing the evaluation process and metrics of indoor location technologies to properly capture these parameters.

In addition, manually evaluating indoor localization technologies proved to be a tedious, time-consuming process. This overhead naturally limits the density of the measurement points and the number of systems that can be evaluated in a reasonable time frame. The initial results from using an automated robot-based benchmarking platform are encouraging, and indicate that such platforms can potentially reduce the evaluation overhead while increasing the fidelity of the evaluation process.

CONCLUSIONS

The 2014 Microsoft Indoor Localization Competition was an experiment that aimed to bring multiple indoor location technologies under the same roof and directly compare their accuracy and overhead requirements. The overwhelming participation clearly demonstrated that indoor location remains a hot topic. It also demonstrated the need from the research and industry community in this area to have a venue for demonstrating its latest results and comparing its performance to other teams in a reliable way. Based on the passion the teams demonstrated and the fun they had during the competition, we believe that more experiments like this one need to take place or even be established as recurring (i.e., yearly) events.

At a high level, the results of the competition helped us draw three concrete conclusions. First, the results showed that the indoor location problem remains unsolved. Both the accuracy and deployment overhead imposed by current technologies cannot enable the indoor location services that the research community has been envisioning. Second, *infrastructure-based* approaches cannot, at this point, deliver the drastic improvement in terms of accuracy that is required to justify their high deployment cost. Third, a way to standardize and automate the evaluation of indoor location technologies in realistic environments is required to allow different technologies to be properly and easily compared and evaluated. ■

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