A Realistic Evaluation and Comparison of Indoor Location Technologies: Experiences and Lessons Learned

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ABSTRACT

We present the results, experiences and lessons learned from comparing a diverse set of technical approaches to indoor localization during the 2014 Microsoft Indoor Localization Competition. 22 different solutions to indoor localization from different teams around the world were put to test in the same unfamiliar space over the course of 2 days, allowing us to directly compare the accuracy and overhead of various technologies. In this paper, we provide a detailed analysis of the evaluation study's results, discuss the current state-of-the-art in indoor localization, and highlight the areas that, based on our experience from organizing this event, need to be improved to enable the adoption of indoor location services.

Categories and Subject Descriptors

C.3 [**Special-purpose and Application-based Systems**]: Real-time and embedded systems

General Terms

Experimentation

Keywords

indoor localization, fingerprinting, ranging, evaluation

1. INTRODUCTION

Accurate indoor localization has the potential to change the way people navigate indoors in the same way the GPS changed the way people navigate outdoors. For well over a decade, academia and industry have recognized the value of the indoor localization problem and have devoted a lot of effort and resources into solving it.

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Infrastructure-free approaches have focused on leveraging already existing WiFi [5, 15, 49, 40, 41, 45, 6, 22, 47, 50], FM and TV [8, 9, 34, 28, 29, 27, 12, 33, 19, 48], GSM [31, 44], geo-magnetic [10], and sound signals [43] to enable indoor localization through detailed fingerprinting. Infrastructure-based approaches rely on the deployment of customized RF-beacons [37], such as RFID [30], infrared [46], ultrasound [36, 20], Bluetooth [7], short-range FM transmitters [26], lights [23], and magnetic signal modulators [32, 2] to enable accurate indoor position estimation.

Even though hundreds of different approaches have been proposed in the literature, the indoor location problem still remains unsolved. 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 hard to draw conclusions about its performance and overhead in realistic conditions. Even worse, this type of evaluation makes 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 the opportunity to different academic and industry groups 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 indoor location to meet and interact with each other, and closely observe the competing solutions in action.

The competition was aggressively advertised through the academia, industry research, and industry startup channels. To motivate participation, cash prizes were awarded to the top performing teams. In response to our call for participation, 36 submissions from 32 teams registered for the competition. Eventually, 21 teams actually participated with 22 systems. The participating teams originated from various countries across Europe, America, and Asia representing a wide variety of technical approaches to the indoor location problem (Table 1). The participating teams came from academia, industry research, and smaller startups in the indoor location space.

	Team	Reference	Team's Affiliation	Technical Approach	Dev. Time (Months)	Global Rank
Infrastructure-Based	1	Bestmann et al. [37]	Lambda:4 Entwicklungen	2.4GHz Phase Offset	60	1
	2	Li et al. [23]	MSR Asia	WiFi+Modulated LEDs	12	4
	3	Adler et al. [3]	Freie Univ. Berlin	2.4GHz Time-of-Flight	72	5
	4	Lazik et al. [20]	CMU	Ultrasonic Time-of-Flight	24	6
	5	Ashok et al. [4]	Rutgers	IR/Radio Time-of-Flight	18	8
	6	Nikodem et al. [42]	Wroclaw Univ. of Tech. MT-Silesia Sp.	2.4GHz Time-of-Flight	5	9
	7	Dentamaro et al. [11]	NextoMe	WiFi+Bluetooth+IMU	24	10
	8	Abrudan et al. [2]	Univ. of Oxford	Modulated Magnetic Signals	24	15
	9	Sark et al. [38]	Humboldt Univ. of Berlin	SDR Time-of-Flight	4	16
	10	Pirkl et al. [32]	DFKI	Modulated Magnetic Signals	90	17
	11	Schmid et al. [39]	Greina Technologies	2.4GHz Phase Offset	24	18
	12	Jiang et al. [17, 18]	Xian Jiaotong Univ.	WiFi+Sound Time-of-Flight	12	21
	13	Selavo et al. [35]	I.E.C.S.	Steerable Antennas ToF	12	22
Infrastructure-Free	14	Klepal et al. [6]	Cork Institute of Technology	WiFi Fingerprinting Bayesian Filter	96	2
	15	Laoudias et al. [22]	Univ. of Cyprus/Cywee	WiFi+IMU Fingerprinting Neural Network	36	3
	16	Zou et al. [52, 51]	Nanyang Tech. Univ.	WiFi Fingerprinting Neural Network	12	7
	17	Ferraz et al. [13]	Ubee S.A.	WiFi+IMU Fingerprinting	9	11
	18	Li et al. [24]	MSR Asia	WiFi+IMU Fingerprinting Particle Filter	24	12
	19	Marcaletti et al. [25]	ETH/IMDEA/Armasuisse	WiFi Time-of-Flight Adaptive Filter	12	13
	20	Xiao et al. [47]	Univ. of Oxford	WiFi+IMU+Maps Conditional Random Fields	12	14
	21	Zhang et al. [50]	Nanyang Tech. Univ.	WiFi+Magnetic Fingerprinting Particle Filter	12	19
	22	Ghose et al. [14]	Tata Consulting Services	WiFi+IMU Fingerprinting Clustering/Decision Trees	3	20

Table 1: The teams that participated in the 2014 Microsoft Indoor Localization Competition. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest). Teams 3 and 4 achieved almost identical location errors (0.005m difference), and we considered this to be a tie. The second place was awarded to Li et al., because they deployed fewer anchor nodes. The column before the last one shows the development time (in months) spent on each system.

In this paper, we describe the competition's evaluation process, provide a detailed analysis of the results, and discuss the experiences and lessons learned from the organization of this competition. In particular, we make the following contributions:

- We provide an in-depth evaluation of the accuracy of 22 different indoor localization systems from academia, industry research and startups in the same realistic, unfamiliar space. We show that sub-meter accuracy is feasible today, and that even WiFi-based approaches can achieve close to $1m$ accuracy.

- We show that the localization accuracy degrades by as much as $3m$ due to setup and environmental changes, such as human or furniture movement and RF interference, between calibration and actual evaluation of the system.

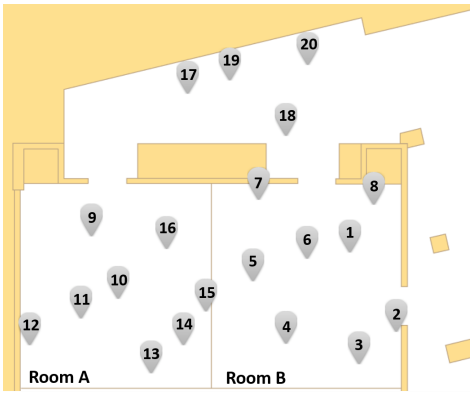
- We compare the expected or previously reported accuracy of each system as determined by controlled lab experiments to the accuracy achieved in our realistic, unfamiliar environment, and show that in practice localization accuracy degrades by $1m - 4m$ on average.

- We show that localization accuracy can widely vary across different evaluation points even for the most accurate systems. In addition, we show that there are easy and hard evaluation points in the sense that most or almost any of the systems can achieve low error respectively. This shows that the choice of evaluation test points is critical, and it reveals the difficulty of objectively evaluating indoor location systems.

- We evaluate the stability of localization accuracy for the top performing systems, and study the promise and limitations of automated, robot-based evaluation.

2. EVALUATION PROCESS

In this section we provide an overview of the systems that participated in the competition, and describe the details of the evaluation process.



(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 $300m^2$ 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 evaluation area and then was used to automatically evaluate the accuracy of the top two teams.

2.1 Participating Teams

Initially 32 teams registered 36 different submissions for the competition. Eventually, 21 teams with 22 different approaches attended the competition (Table 1). All systems 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 to compute indoor locations, apart from existing WiFi infrastructure. Most of these approaches leverage existing WiFi signals and combine them with sensors, such as 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, custom RF transmitters and more.

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

Most of the participating teams were able to setup their systems according to their expectations. However, a few teams faced difficulties that might have negatively impacted their performance. In particular, Team 11 erroneously measured the ground truth location of one of their anchor nodes, leading to much higher than expected localization error. For various reasons, Teams 13 and 18 spent only a limited amount of time setting up, and this resulted into suboptimal system configurations. Finally, Team 20 faced technical issues that prevented it from using wearable inertial sensors, thus negatively impacting its overall accuracy.

2.2 System 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 $10m$ by $9m$ in dimensions, and the hallway in front of the two rooms (measuring approximately $10m$ by $4m$) were used for the evaluation. Figure 1 shows the floor plan of the approximately $300m^2$ evaluation area. None of the participating teams had access to the evaluation area before the competition.[1]

The competition was a 2-day event. During the first day, all teams were given 7 hours to setup 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 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

[1]A demo video made by one of the competing teams [22] showing the hallway and Room A in Figure 1(c) can be seen at: `http://youtu.be/gQBSRw6qGn4`

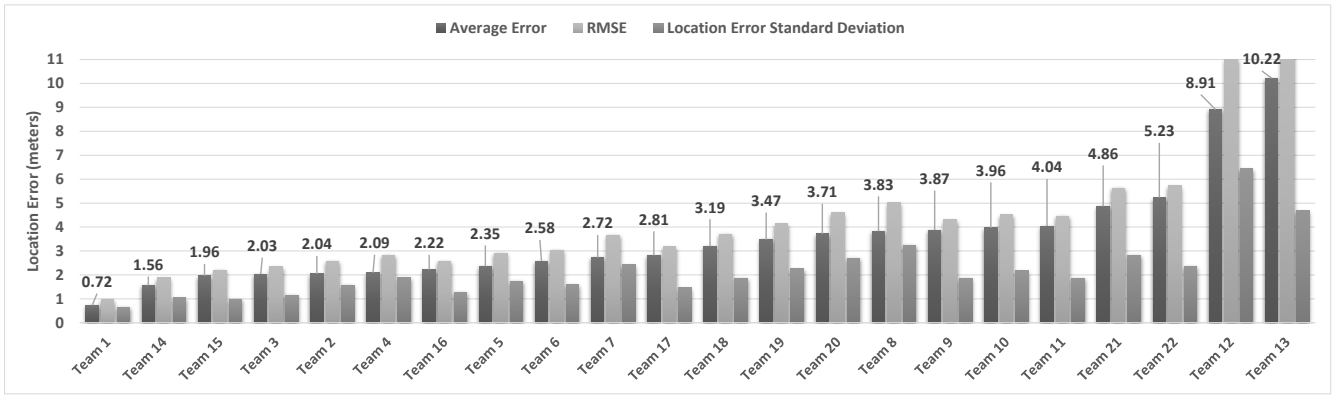


Figure 2: Average location error, root mean square error(RMSE), and the standard deviation of the location error for all 22 teams. As a reference, if a team were to always report the center of the evaluation area as the true location, the average location error would be 7 meters.

were mounted on cocktail tables like the ones shown in Figure 1(b) at a height of approximately 1.5 meters from the ground. All the teams that relied on generic WiFi access points for estimating indoor location, could only use these access points.

Note that the deployment of 10 dedicated WiFi access points created a bias in favor of all systems in the *infrastructure-free* category. Given the relatively small size of the evaluation area, deploying 10 access points resulted into an unusually high density of access points. Most areas today (i.e., malls) provide fewer number of access points that are also mounted differently in the space (i.e., mounted on the ceiling).

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., $(2.12m, 5.1m)$) 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. Leveraging the technical drawings of the building used for the evaluation, we verified that the evaluation points were measured with centimeter level accuracy ($1 - 2cm$ error). This measurement error is an order of magnitude less than the localization error achieved by the best team, and thus it did not affect the evaluation results.

During the second day of the evaluation, each team would show up at a pre-assigned time slot, turn on its deployed system, and hand the device to be localized to the organizers. The device was a mobile phone, a tablet or a laptop depending on the system under test. The organizers carried the device above each of the 20 evaluation points, waited for a couple of seconds, and recorded the location 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. Note that even though we recorded location estimates only on the pre-measured 20 evaluation points, the system under test was allowed to continuously perform localization. For instance, the system under test could use inertial sensors to perform continuous path tracking to improve localization accuracy.

2.2.1 Introducing Realistic Uncertainty

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

2.3 Automated 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 benchmark-

ing platform [16] to automatically evaluate the localization accuracy of the two teams in the infrastructure-based and infrastructure-free categories that achieved the lowest localization errors.

The EVARILOS benchmarking platform is an integrated experimental infrastructure that fully automates the evaluation of indoor localization systems [21]. 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 setup day, the TWISTbot platform was able to automatically extract the floor plan of the evaluation area using its onboard sensors (Figure 1(f)). During the evaluation day, 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 participating teams.

This allowed us to evaluate the stability of the localization accuracy for the top performing systems, and to study the promise and limitations of robot-based evaluation.

3. LOCALIZATION ACCURACY ANALYSIS

Figure 2 shows the localization accuracy of all 22 systems. The average location error achieved varied between $0.72m$ and $10.22m$. Only 3 teams were able to achieve less than $2m$ accuracy, while half of the teams achieved less than $3m$ error. The team with the highest accuracy was Team 1 with an average location error of $0.72m$. It is worth noting that Team 1 opted to deploy only 6 out of the total 10 anchor nodes they were allowed to deploy in the evaluation area.

In the infrastructure-based category, Team 1 was followed by Team 2, Team 3, and Team 4, with all 3 teams achieving almost identical location errors ($2m$ - $2.1m$). Teams 3 and 4 deployed 10 anchor nodes, while Team 2 deployed only 5 LED lamps.

In the infrastructure-free category, Team 14 achieved the lowest location error ($1.6m$). Teams 15, 16, and 17 followed with location errors of $1.96m$, $2.22m$, and $2.81m$ respectively.

Interestingly, the gap in terms of location accuracy between infrastructure-free and infrastructure-based approaches seems to be significant only for the top performing teams. The most accurate infrastructure-based approach (Team 1) was able to achieve half the error of the top infrastructure-free approach (Team 14), which represents a notable increase in localization accuracy.

Figure 3(a) shows the empirical CDF of the location errors for the top 4 teams in both categories. The top approaches in both categories (Team 1, and Team 14) 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 ($\approx 0.5m$). Also, the maximum location errors produced by infrastructure-based approaches can be higher than that of infrastructure-free approaches.

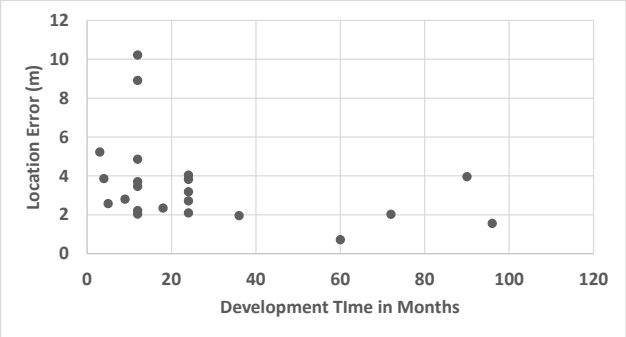


Figure 4: Relationship between the achieved location error in meters and the development time spent on each system.

Figure 5 shows the exact location error that the top 4 teams in each category achieved for all 20 evaluation points. Note that the location error achieved by each team varies across evaluation points. In addition, the top teams do not necessarily achieve the best performance for all evaluation points. For instance, Team 14 (the top infrastructure-free approach) achieves the worst or close to the worst location error compared to the other teams for several evaluation points (1, 2, 11, 15, 18).

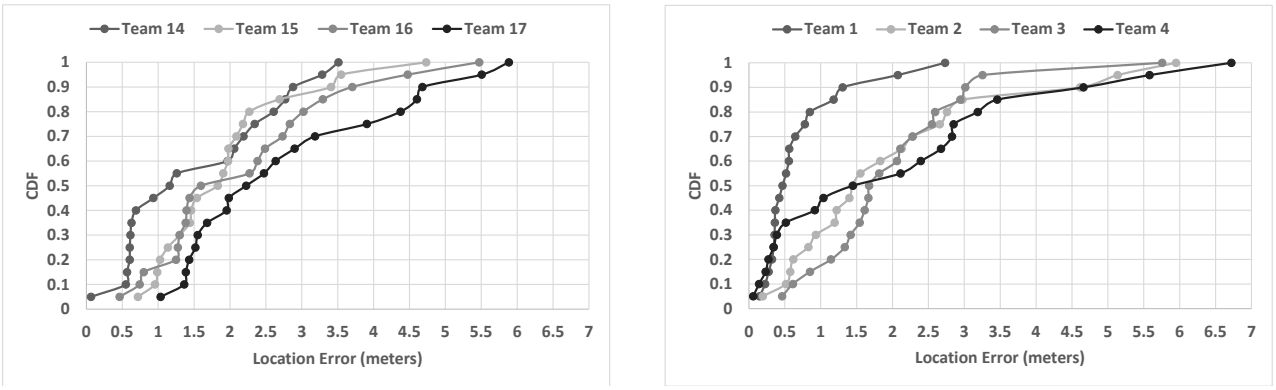
3.1 Implementation Variations

Even though different teams leveraged similar techniques for indoor location estimation, the variance in performance 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 $0.72m$ (Team 1) all the way to approximately $4m$ (Team 11). Similarly, WiFi-only approaches exhibited similar variations ranging from $1.6m$ (Team 14) to approximately $5m$ (Team 22) location accuracy. On the other hand, the two teams that leveraged modulated magnetic signals (Team 8 and Team 10) achieved similar accuracy ($\approx 4m$).

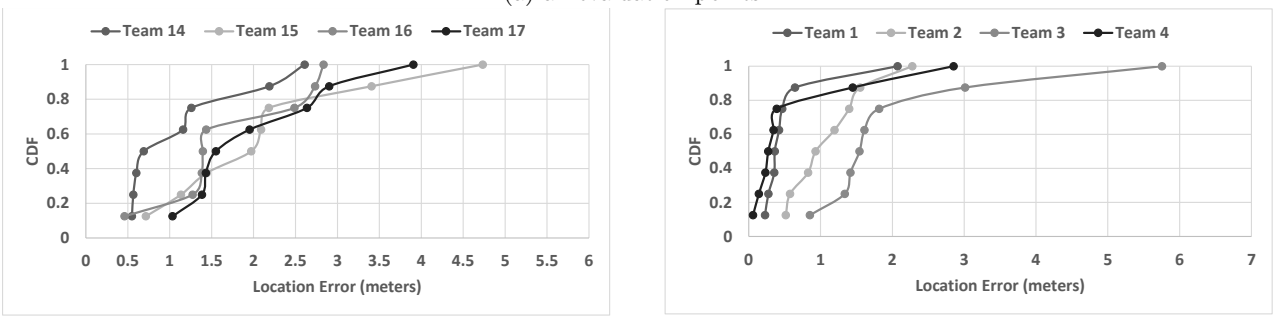
We believe that some of these variations can be attributed to the amount of time that the teams have devoted in implementing their approaches. As shown in Table 1, Team 1 has spent 5 years optimizing its infrastructure-based system, while Team 11 has only been working on its implementation for two years. Similarly, in the case of infrastructure-free approaches, Team 14 has spent 8 years developing its system, while Team 22 has devoted only 3 months.

In some cases, though, development time does not seem to help. For instance, even though Team 10 has spent almost 5 years on indoor localization using modulated magnetic signals, Team 8 achieved similar performance using the same technology after 2 years of development time.

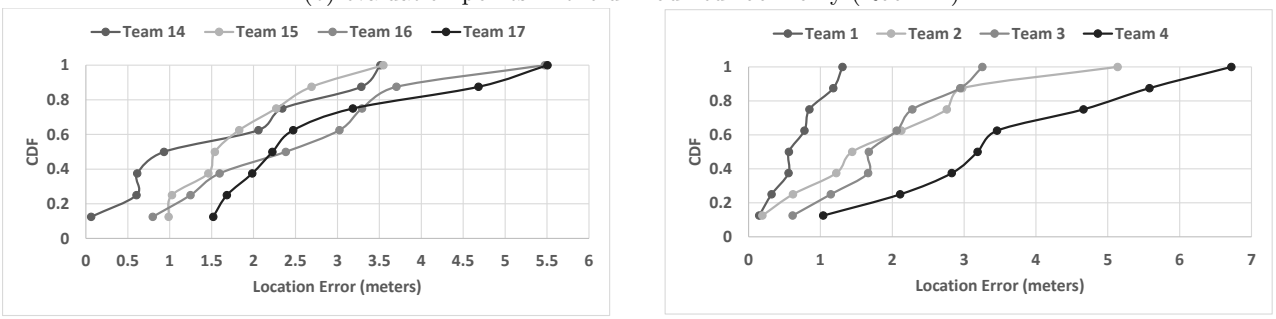
Figure 4 shows the localization accuracy achieved by each team as a function of the development time. Even though some relatively young systems performed well, it is clear that the variation in performance is higher when the development time is less than 2 years. The only teams that were able to achieve localization errors lower than $2m$ had devoted more than 5 years of development time.



(a) all evaluation points



(b) evaluation points in the unmodified room only (Room A)



(c) evaluation points in the modified room only (Room B)

Figure 3: Empirical cumulative distribution function of the location error for the top 4 teams in the infrastructure-free (left) and infrastructure-based (right) categories.

3.2 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 Team 15, 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 $0.47m$ and $0.94m$.

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 Team 3, exhibited an increase in location errors in the modified room that varied anywhere between $0.11m$ and $2.99m$. For Teams 1 and 3 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, Team 2 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.

This intuition can be further verified by Figure 3(b), and Figure 3(c), where the empirical CDF of the location error for the top 4 teams is shown for each room separately. All CDF curves for the infrastructure-free approaches seem to be uniformly shifted to the right in the case of modified furniture. However, for infrastructure-based approaches this shift is significantly smoother and varies across systems. We believe that this variability across teams is caused by the type of deployment decisions made by each team as described earlier.

Figure 5 shows a more detailed view on the impact that the furniture setup has on the location accuracy of the top 4 teams in each category. The errors for the evaluation points in the room with the modified furniture (first 8 points) are

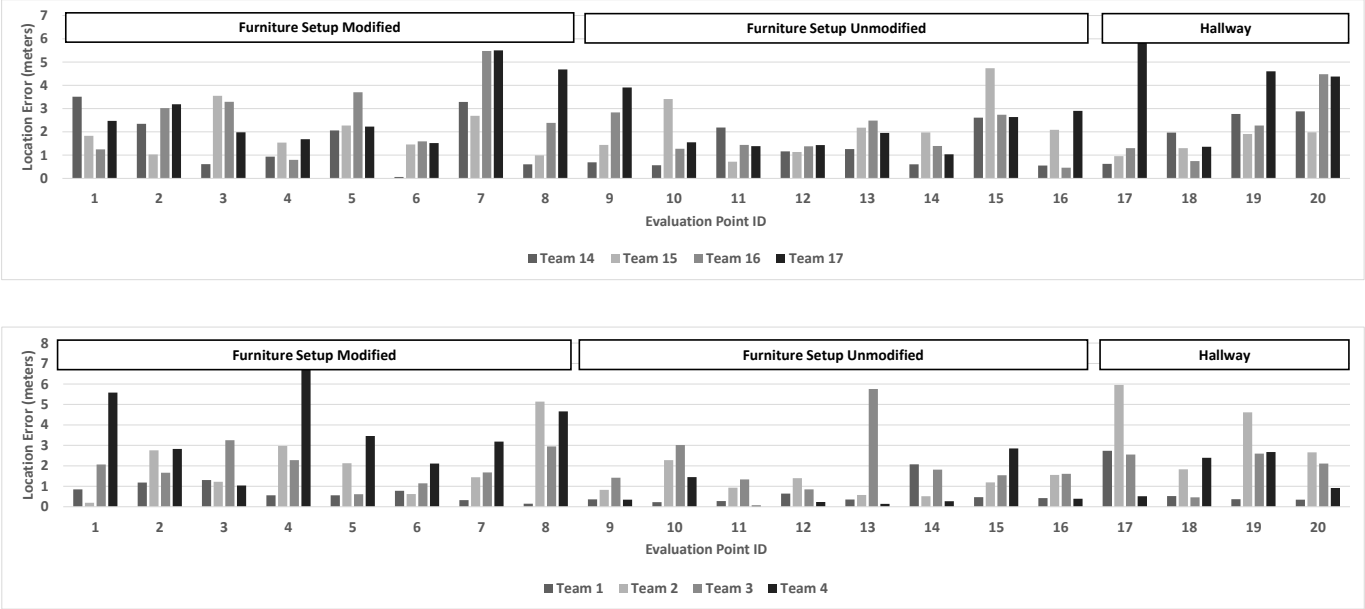


Figure 5: Location error achieved at each evaluation point by the top 4 teams in the infrastructure-free (top) and infrastructure-based categories (bottom).

Approach	Avg. Location Error (meters)	
	Identical Room	Modified Room (Room B)
Infrastructure-free		
Team 14	1.2	1.67
Team 15	2.21	1.92
Team 16	1.75	2.69
Team 17	2.09	2.91
Infrastructure-based		
Team 1	0.6	0.71
Team 2	1.15	2.06
Team 3	2.16	1.95
Team 4	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 significant increase in location error in the room where the furniture location and orientation was modified.

significantly higher compared to the evaluation points in the room with the unmodified furniture (points 8 through 16).

Note that the error for the evaluation points in the hallway also increases. We believe that this was caused by the limited coverage that most teams' equipment provided at the hallway. During setup, most teams emphasized deployment in the interior of the two rooms, creating blind spots in the hallway.

3.3 Error Correlation Between Teams

In this section we examine the correlations of the different teams in terms of their performance across the evaluation points. For each team, a vector including the localization error for each of the 20 evaluation points was calculated. We analyze the correlation of each pair of teams by computing the cross-correlation between their localization error vectors.

Figure 6 shows the computed correlation matrix for all 22 teams. There is a clear subset of teams that are highly correlated. First, the top 4 WiFi-based fingerprinting teams (Teams 14, 15, 16, and 17) are highly correlated. Surprisingly, Team 22 is also highly correlated to these teams even though it achieved almost double the localization error. Even though less accurate, this team achieved similar trends in localization error across evaluation points.

Even more surprisingly, the top WiFi-fingerprinting approaches seem to be highly correlated to the the top 4 infrastructure-based teams (Teams 1, 2, 3, and 4) despite the fact that some of these teams are using completely different technology (i.e., Team 4 leverages ultrasonic transmissions).

3.4 Variance Across Evaluation Points

Figure 7 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 accuracy. For instance, points 6, 9, 10, 11, 12, and 16 tend to generate lower location errors across all teams 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.

This indicates that there are points that almost any system can estimate accurately, and there are points that almost any system can have a hard time estimating accurately. This information can be rather useful when evaluating the performance of indoor localization techniques. We believe that proper evaluation metrics should be defined that are

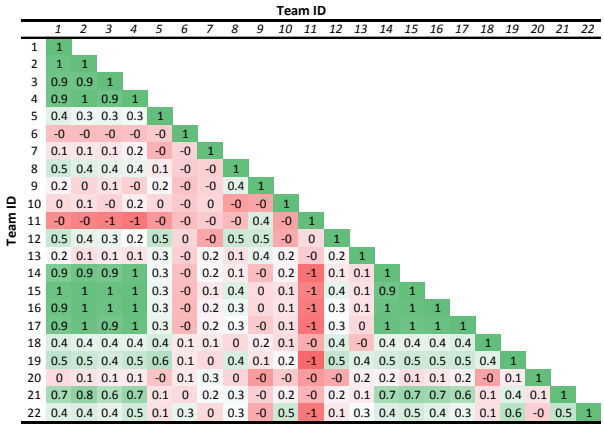


Figure 6: The cross-correlation of the localization accuracy vectors for every pair of systems evaluated.

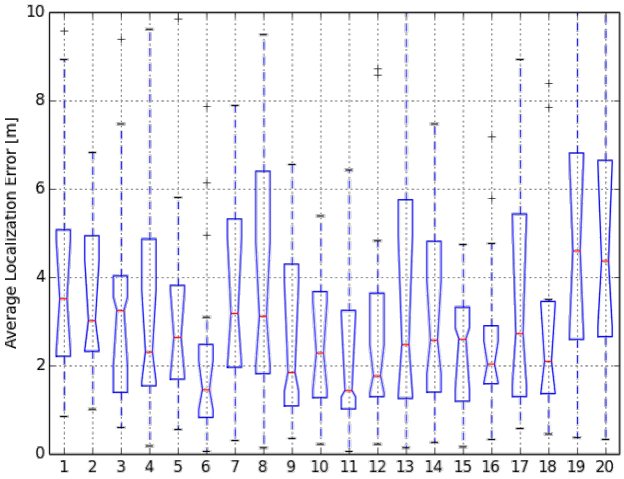


Figure 7: Average location error and its standard deviation across all teams for each of the 20 evaluation points.

able to emphasize more on the hard to estimate locations in the area of interest. How these metrics are specifically defined is beyond the scope of this study.

3.5 Lab vs. Reality

Indoor localization approaches are usually evaluated in highly controlled environments (i.e., research lab). This type of evaluation could positively bias the performance of the system. To quantify this bias, we asked each participating team to report the localization error that it had previously achieved in their own experiments, and compared this error to the one achieved in our evaluation study.

Figure 8 shows the difference between expected and achieved localization error for all teams. Most teams achieved worse accuracy by approximately $1.5m$ to $4m$. There were teams though (i.e., Team 1, Team 14, Team 17) that were able to achieve the same or even better accuracy than expected. Note that all the teams that achieved higher than expected accuracy are WiFi-based approaches (Teams 14, 17, 18). We believe that this was due to the large number of WiFi access points that were leveraged in the evaluation study. Given that the evaluation area was relatively small ($300m^2$), all 10 access points could be successfully sniffed from every location in the evaluation area, creating an ideal setup for WiFi-based approaches.

3.6 Robot-based Evaluation

The best two teams (Teams 1 and 14), as determined by the manual evaluation process, were invited to another evaluation round using the EVARILOS benchmarking platform described in Section 2.3.

Table 3 shows the average location error for both the robot and the manual evaluation process. Surprisingly, the approach by Team 1 was able to achieve the exact same localization accuracy indicating the stability and reliability of the technology. The accuracy of the approach by Team 14 was only slightly increased by $0.15m$. 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

Approach	Avg. Location Error (meters)	
	Manual	Robot
Team 1	0.72	0.72
Team 14	1.56	1.71

Table 3: Automatic evaluation using the EVARILOS benchmarking platform. For Team 14, 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 all evaluation points.

area was a very challenging navigation and locomotion environment due to the presence of a 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 an average positioning error of less than $25cm$. This result highlights the promising potential of leveraging robots 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. However, scaling out automated, robot-based evaluation to any type of floor-plan that might include multiple floors with different locomotion conditions still remains a challenging, unsolved problem.

4. LESSONS LEARNED

This evaluation study 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

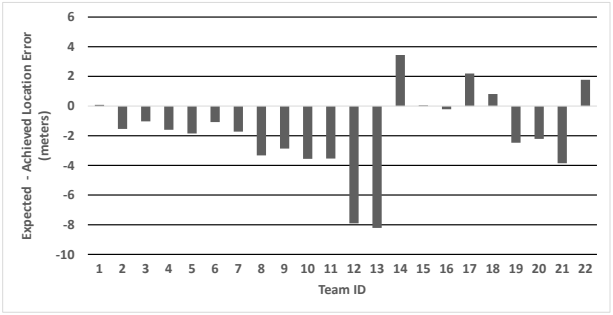


Figure 8: The difference between expected (previously measured in the lab) and achieved location accuracy in meters. Negative values indicate worse accuracy than expected while postitive values indicate better than expected results.

experience organizing this event, we believe we can safely extract a set of high level conclusions.

4.1 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 Team 14 managed to achieve an impressive 1.6 meters accuracy solely based on off-the-shelf access points (the high density of deployed access points positively biased this type of systems), and Team 1 was able to achieve 0.72 meters 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. In addition, there does not seem to be a technology that can consistently provide the same localization error across all evaluation points. All systems exhibited large accuracy variations across different evaluation points which raises concerns about the stability/reliability of current indoor location technologies.

4.2 Deployment Overhead Remains High

Most of the teams that participated in the evaluation study 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, 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. On average, it took each team 5 hours to setup its approach in the designated evaluation area. 8 out of the total 22 teams made use of the full 7 hours of setup time, and for a couple of teams 7 hours was not enough time to fully deploy their systems. 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 hide 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.

4.3 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 $1.6m$. 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 0.5m or even no increase in error at all when the furniture setup is altered.

4.4 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, 95^{th} percentile etc.), there are variations in the real world that are not being properly captured by these metrics. For instance, as Figure 7 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.

4.5 Designing Future Indoor Localization Competitions

Our first attempt at organizing an indoor localization competition gave us a lot of insight on how an ideal competition should be organized. First, one of the major issues that teams had to deal with was the RF interference caused by the numerous custom RF solutions that were simultaneously deployed. This interference made calibration a tedious task, and in some cases it prevented contestants from properly calibrating their systems. Ideally, and assuming no realistic time restrictions, each team should be allocated a time slot during which only this team's system is active, enabling hassle-free system calibration.

Second, in this competition dedicated access points were deployed just for the competition to make sure that contestants can easily measure their ground truth locations. However, any infrastructure-free approach should be able to rely on existing access points, and should also be able to deal with all the different sources of noise that this implies (i.e., lower deployment density, power level adaptation etc.).

Third, instead of using a relatively small area consisting of two large rooms on a single floor, a significantly larger area with a mixture of open and office-like spaces across multiple floors should be leveraged for such an evaluation.

Fourth, the evaluation of systems in this competition has been point-based ignoring the ability of these systems to perform continuous localization as the human subject moves in space and time. A way to capture and quantify the ability of indoor location systems to capture the continuous path that the human subject follows would be of great value.

Fifth, to ensure that all systems are evaluated under identical environmental conditions (i.e., number of people in the room, interference etc.), all systems should be simultaneously evaluated at a given evaluation point. Also, in order to capture temporal variations, all systems should be evaluated across different time windows as well.

Sixth, it is very hard to capture the effectiveness of an indoor localization algorithm with a single metric. Ideally, competing systems should be compared across a wide variety of localization accuracy metrics, and several other aspects of each system, such as deployment overhead, setup time, and more, should be quantified in detail.

5. CONCLUSIONS

The indoor location competition described in this paper 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 event, we believe that more experiments like this one need to take place or even be established as recurring (i.e., yearly) events.

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