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The Microsoft Indoor Localization Competition

Experiences and lessons learned

We present the results, experiences, and lessons learned from comparing a diverse set of indoor location technologies during the Microsoft Indoor Localization Competition. Over the last four years (2014–2017), more than 100 teams from academia and industry deployed their indoor location solutions in realistic, unfamiliar environments, allowing us to directly compare their accuracies and overhead. In this article, we provide an analysis of this four-year-long evaluation study's results and discuss the current state of the art in indoor localization.

Overview of the indoor location problem

Accurate indoor localization has the potential to transform the way people navigate indoors in the same way the global positioning system (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 much effort and resources into solving it. Infrastructure-free approaches have focused on leveraging already existing Wi-Fi [1]–[10], frequency modulation (FM) and TV [11]–[18], global system for mobile communication [19], [20], geomagnetic [21], and sound signals [22] to enable indoor localization through detailed fingerprinting. Infrastructure-based approaches rely on the deployment of customized radio-frequency (RF) beacons [23], such as RF identification [24], infrared [25], ultrasound [26], [27], Bluetooth [28], short-range FM transmitters (Tx) [29], lights [30], and magnetic signal modulators [31], [32] 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 it hard to draw conclusions about its performance and overhead in realistic conditions. Even worse, this type of evaluation makes comparisons of different indoor location solutions almost impossible.

With this in mind, we organized the Microsoft Indoor Localization Competition [33]–[37]. The main motivation behind the competition was to give the opportunity to different academic and industry groups to test their indoor

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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 academia, industry research, and industry startup channels. To motivate participation, cash prizes were awarded to the top performing teams. Over the past four years (2014–2017), we had the opportunity to closely observe and evaluate more than 100 teams from various countries across Europe, the United States, and Asia representing a wide variety of technical approaches to the indoor location challenge (Tables 1 and 2). The participating teams came from academia, industry research, and smaller startups in the indoor location field.

Indoor location technology fundamentals

In this section, we present a brief overview of the major classes of technologies used in indoor localization. The purpose is to provide some fundamental technical background information that can be used to better understand what type of indoor location systems were built by the different teams that participated in the competition.

At a high level, indoor location technologies can be classified into two categories based on their hardware requirements. On the one hand, there are all the systems that rely on the capabilities of commercial off-the-shelf hardware. These are software-only systems where location computation relies on the radios (Wi-Fi, Bluetooth, FM, and so on) and sensors (gyro, accelerometer, compass, and so forth) typically found embedded in devices like phones and tablets.

On the other hand, there are hardware-based systems where location computation relies on the deployment of custom hardware such as ultrawideband (UWB) and ultrasound. This type of system operates in a very similar way to GPS. In the case of GPS, a network of accurately time-synchronized satellites orbits around Earth. Each satellite orbits on a predetermined path, allowing us to know exactly where it is located at any given time. Each satellite continuously transmits a unique signal that, when received by a GPS receiver, allows the receiver to calculate its distance to the satellite. Given that the locations of the satellites are known at any given time, if the GPS receiver can estimate its distance to at least four satellites, it can calculate its location using techniques such as triangulation [1] and multilateration [38].

Because GPS signals are very weak indoors, researchers have proposed the deployment of custom hardware that, in a way, aims to recreate an indoor satellite network. Each installed custom hardware device acts as a virtual satellite. It is deployed at a known ground truth location, and it can wirelessly communicate with any device that wants to be localized. The purpose of this communication is to allow the unlocalized device to estimate its distance to the virtual satellite. Given distance estimates to at least three virtual satellites, the unlocalized device can use the same triangulation [1] and/or multilateration [38] techniques to estimate its position in the indoor environment. Most of the techniques in this category focus on how to engineer the transmitted wireless signals to enable the most accurate possible distance estimation between a virtual satellite and the unlocalized device.

Software-based approaches to indoor location

The most widely adopted approach in software-only indoor localization is wireless fingerprinting [1]–[10]. Wireless fingerprinting leverages the available wireless transceivers (i.e., Wi-Fi, Bluetooth, and so on) on devices like phones and tablets along with already deployed networking infrastructure (i.e., Wi-Fi networks) to perform indoor localization. This approach requires an offline training stage and an online positioning stage, as shown in Figure 1. The training stage is responsible for collecting location-annotated wireless signal fingerprints that form the fingerprint database. To collect a Wi-Fi signal fingerprint, a mobile device, such as a mobile phone or a tablet, simply scans all visible Wi-Fi access points and records the received signal strength indicator (RSSI) or channel state information for each one of them. The collection of access point IDs and their corresponding RSSI values forms the wireless fingerprint. Each wireless fingerprint is annotated with the ground truth location where it was recorded, usually through a tedious and time-consuming manual surveying process of the indoor environment. In some cases, ground truth location information can be automatically crowdsourced through user activity, such as business check-ins (Figure 1). At the end of this process, a database of wireless fingerprints associated to ground truth locations is generated. The central concept behind this process is that the set of visible wireless access points varies across locations and therefore can be used to differentiate locations indoors. In addition, the RSSI values for different access points vary across locations, helping to further differentiate locations in the indoor environment.

In most cases, wireless fingerprints also include the fluctuations in the magnetic field as recorded by the compass sensor embedded in most phones and tablets today [21]. The main idea is that the internal structure of buildings, especially that of buildings with metallic skeletons, introduces noise in the magnetometer readings. This noise depends on where exactly in the building the readings are taken and therefore carries location-discriminating information. As a result, most fingerprinting approaches will always reside on fingerprints that include Wi-Fi and magnetic information.

At the online positioning stage, the mobile device that needs to be localized records its wireless signal fingerprint and compares it against the available fingerprints in the database. The location associated to the fingerprint in the database that is the closest to the fingerprint recorded on the mobile device, in terms of a distance metric, such as Euclidean distance, is assumed to be the current location of the device. The most accurate implementations of wireless fingerprinting reside on machine-learning techniques, such as neural networks and Bayesian inferencing, instead of simple distance metrics to compare fingerprints. To enable accurate

Table 1. The teams that participated in the 2014 and 2015 Microsoft Indoor Localization Competitions. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest) that year.

	Team	Team's Affiliation	Country	Technical Approach	Global Rank
2014					
Infrastructure based	Reimann et al. [51]	Lambda:4	Germany	2.4-GHz phase offset	1
	Li et al. [30]	Microsoft Research	China	Modulated light-emitting diodes (LEDs)	4
	Adler et al. [52]	Freie Universität Berlin	Germany	2.4-GHz time of flight (ToF)	5
	Lazik and Rowe [27]	Carnegie Mellon University	United States	Ultrasonic ToF	6
	Ashok et al. [43]	Rutgers University	United States	Infrared/radio ToF	8
	Nikodem et al. [53]	Wroclaw University of Science and Technology	Poland	2.4-GHz ToF	9
	Dentamaro et al. [54]	Nextome	Italy	Wi-Fi + Bluetooth + inertial measurement unit (IMU)	10
	Abrudan et al. [55]	University of Oxford	United Kingdom	Modulated magnetic signals	15
	Sark and Grass [56]	Humboldt University of Berlin	Germany	Software-defined radio ToF	16
	Pirkl and Lukowicz [42]	German Research Center for Artificial Intelligence	Germany	Modulated magnetic signals	17
	Schmid and Lee [57]	Greina Technologies	United States	2.4-GHz phase offset	18
	Jiang et al. [58]	Xian Jiaotong University	China	Wi-Fi + sound ToF	21
	Selavo et al. [59]	Institute of Electronics and Computer Science	Latvia	Steerable antennas ToF	22
Infrastructure free	Beder and Klepal [7]	Cork Institute of Technology	Ireland	Wi-Fi fingerprinting	2
	Li et al. [8]	University of Cyprus	Cyprus	Wi-Fi + IMU fingerprinting	3
	Zou et al. [60]	Nanyang Technological University	Singapore	Wi-Fi fingerprinting	7
	Ferraz et al. [61]	Ubee	Brazil	Wi-Fi + IMU fingerprinting	11
	Li et al. [62]	Microsoft Research	China	Wi-Fi + IMU fingerprinting	12
	Marcaletti et al. [63]	Swiss Federal Institute of Technology/ Madrid Institute of Advanced Studies/ Armasuisse	Switzerland/Spain	Wi-Fi ToF	13
	Xiao et al. [9]	University of Oxford	United Kingdom	Wi-Fi + IMU + maps	14
	Zhang et al. [10]	Nanyang Technological University	Singapore	Wi-Fi + magnetic fingerprinting	19
	Ghose et al. [64]	Tata Consulting Services	India	Wi-Fi + IMU fingerprinting	20
2015					
Infrastructure based	Lazik and Rowe [27]	Carnegie Mellon University	United States	Ultrasonic ToF	2
	Time Domain [49]	Time Domain	United States	UWB	3
	Kempke et al. [65]	University of Michigan	United States	UWB	4
	Quantitec Intranav [66]	Quantitec IntraNav	Germany	UWB	5
	Simon et al. [67]	University of Pannonia	Hungary	Modulated LEDs	6
	Klipp et al. [68]	Fraunhofer FOCUS	Germany	IMU + visual markers	7
	Chen et al. [69]	Nanyang Technological University/ University of California, Berkeley	Singapore/United States	IMU + Bluetooth low-energy (BLE) beacons	8
	Von Zengen et al. [70]	Technical University Braunschweig	Germany	2.4-GHz phase measurements	9
	Symington et al. [71]	University College London/University of California, Los Angeles	United Kingdom/ United States	Wi-Fi + magnetic + ToF	12
	Pirkl and Lukowicz [42]	DFKI	Germany	Modulated magnetic signals	14

(continued)

Table 1. The teams that participated in the 2014 and 2015 Microsoft Indoor Localization Competitions. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest) that year. (*continued*)

	Team	Team's Affiliation	Country	Technical Approach	Global Rank
	Maróti et al. [72]	University of Szeged	Hungary	Radio interferometry	16
	Lin et al. [73]	National Chiao-Tung University	Taiwan	Mobile device encounterings	17
	Nikodem et al. [53]	Wroclaw University of Science and Technology	Poland	2.4-GHz ToF	19
	Deora and Krishnamachari [74]	University of Southern California	United States	Zigbee beacons	20
	Kuo et al. [47]	University of Michigan	United States	Visible light	21
	Mirshekari et al. [75]	Carnegie Mellon Unversity	United States	Structural vibration	22
Infrastructure free	Sánchez et al. [45]	European Commission, Joint Research Center	Italy	Lidar	1
	SPIRIT Navigation [76]	SPIRIT Navigation	Russia	Wi-Fi + magnetic + IMU fingerprinting	10
	Guimarães et al. [39]	Fraunhofer Research Center	Portugal	Wi-Fi + magnetic + IMU fingerprinting	11
	Zou et al. [60]	Nanyang Technological University/ University of California, Berkeley	Singapore/United States	Wi-Fi + IMU fingerprinting	13
	Wu et al. [77]	University of Windsor	Canada	Wi-Fi + IMU fingerprinting	15
	Herrera et al. [78]	Navix	Mexico	Wi-Fi + IMU fingerprinting	18
	Ghose et al. [64]	Tata	India	Wi-Fi + IMU fingerprinting	23

localization, fingerprints need to be carefully engineered so that even nearby locations have sufficiently different fingerprints. To do so, researchers have exploited more physical layer signal quality indicators that go beyond RSSI [i.e., signal-to-noise ratio (SNR), frequency offset, and more] and have also expanded fingerprints to include widely available wireless signals that go beyond Wi-Fi, such as FM and TV signals [11]–[18] (Figure 1).

The major challenges in implementing wireless fingerprinting are the overhead of the manual process for building the fingerprint database and the inherent noise in the wireless signals that can affect localization accuracy. Wireless signals change over time, and they are affected by the number of people in the indoor environment as well as by the placement of big objects, such as furniture. In addition, access points disappear or appear continuously, affecting the stability of wireless fingerprints.

An alternative to wireless fingerprinting is pedestrian dead reckoning (PDR) [39]. PDR leverages the on-board sensors of mobile devices, such as accelerometers, gyro, and compass, to count the steps and turns of the person holding the device. Assuming the person entered the indoor environment at a known point (i.e., entrance to a shopping mall), the number of steps and turns the person took can be used to estimate his or her location in the space at any given time. If the map of the indoor environment is available, PDR-based techniques can achieve higher accuracy by constraining human movement based on the map.

The major challenge with PDR is that sensor data tend to drift over time. Even though initially very accurate, as the person continuously moves, the noise in the inertial sensors accumulates over time, impacting the overall localization accuracy. More recently, PDR techniques have been used in a complementary way to wireless fingerprinting. The inertial sensor data is used to filter out noise in the wireless fingerprints and vice versa, leading to more reliable indoor localization.

Hardware-based approaches to indoor location

Ranging primitives

Hardware-based approaches rely on ranging, the process of estimating the distance between two devices (i.e., between the device that needs to be localized and one of the custom hardware devices that have been preinstalled in known locations). Figure 2 shows the three fundamental techniques used for estimating this distance. In all cases, distance estimation is achieved by accurately timestamping the transmission and reception of wireless signals exchanged between the participating devices. To accurately timestamp these signals, all participating devices need to be tightly time synchronized.

The most common way of estimating the distance between two devices [Tx and receivers (Rx) in Figure 2] is for these devices to measure the ToF of a single wireless transmission. By timestamping the wireless signal at the time of tranmission (t_1 in Figure 2) and at the time of reception (t_2 in Figure 2), one can measure the ToF, the time it takes the wireless signal to travel from one device to the other. If the speed at which the

Table 2. The teams that participated in the 2016 and 2017 Microsoft Indoor Localization Competitions. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest) that year.

	Team	Team's Affiliation	Country	Technical Approach	Global Rank
2016					
Infrastructure based	Leica [46]	Leica	Germany	Cameras + GPS + lidar	Exhibition
	RealEarth [79]	RealEarth	United States	Lidar	1
	Quantitec Intranav [66]	Quantitec IntraNav	Germany	UWB	2
	Lou and Peng [80]	Hangzhou Sunsend Info Tech Co. Ltd	China	UWB	3
	Dobrev et al. [44]	Friedrich-Alexander-Universität	Germany	24-GHz radar	4
	Sequitur [81]	University of Bologna, Uniset LLC, DMM LLC	Italy	UWB	5
	Kämäräinen et al. [48]	VTT Technical Research Centre of Finland Ltd.	Finland	UWB impulse radar	6
	Tabarovsky et al. [82]	RTLS Research and Development LLC	Russia	UWB	7
	Hammer et al. [41]	Linz Center of Mechatronics GmbH	Austria	Sound ToF	9
	Kulm et al. [83]	Eliko	Estonia	UWB	12
	Hoppe et al. [50]	Freiburg im Breisgau/ Telocate GmbH	Germany	Sound time difference of arrival (TDoA)	13
	Wang et al. [84]	Zhejiang University	China	Sound TDoA	16
	Flores et al. [85]	Friedrich-Alexander-Universität	Germany	Ultrasound	17
	Baszun et al. [86]	Biocontrol	Poland	UWB	19
	Cabuz et al. [87]	Jacobs University Bremen/ ZIGPOS GmbH	Germany	Zigbee + super multidimensional scaling	23
	Vadeny et al. [88]	University at Albany	United States	Visual simultaneous localization and mapping and visible light communication	26
Infrastructure free	Guimarães (initialization) et al. [39]	Fraunhofer Research Institute	Portugal	Wi-Fi + magnetic + IMU	8
	Shu et al. [89]	Tongji University	China	Wi-Fi + magnetic + IMU fingerprinting	10
	Guimarães et al. [39]	Fraunhofer Research Institute	Portugal	Wi-Fi + magnetic + IMU	11
	Huang and Yang [90]	Ubirouting	China	Wi-Fi + magnetic + IMU fingerprinting	14
	Wu et al. [91]	Glodon Software	China	Wi-Fi + magnetic + IMU fingerprinting	15
	Rea et al. [92]	IMDEA Networks Institute/ Armasuisse	Spain/ Switzerland	Wi-Fi ToF	18
	Mosharafa et al. [93]	Nile University	Egypt	Wi-Fi + magnetic + IMU fingerprinting	20
	Yoshizawa et al. [94]	Ricoh	Japan	Bluetooth beacons + IMU	21
	Han et al. [95]	Korea Advanced Institute of Technology	South Korea	Wi-Fi + magnetic + IMU fingerprinting	22
	Shu (init.) et al. [96]	Zhejiang University	China	Wi-Fi fingerprinting	24
	Schmitz et al. [97]	Affiliation	Germany	Wi-Fi + IMU fingerprinting	25

(continued)

Table 2. The teams that participated in the 2016 and 2017 Microsoft Indoor Localization Competitions. Teams in each category are listed in order of the localization accuracy they achieved (highest to lowest) that year. (*continued*)

	Team	Team's Affiliation	Country	Technical Approach	Global Rank
2017					
Infrastructure based	RealEarth (init.) et al. [79]	Kaarta	United States	Lidar	1
	Quantitec Intranav [66]	Quantitec Intranav	Germany	UWB	2
	Beuchat et al. [98]	ETH	Switzerland	UWB	3
	Chen et al. [69]	King Abdullah University of Science and Technology	Saudi Arabia	Sound	6
	Cheng and Guan [99]	Kiwii Power Technology Corporation	United States	UWB	7
	Snyder et al. (init.) [100]	Astrobotic	United States	Lidar	10
	Wang et al. [101]	McMaster University	Canada	Sound	11
	Acton and Kulkarni [102]	Arin Technologies	United States	UWB	12
	Hemamali and Sreenivas [103]	Trackray	India	UWB	13
Infrastructure free	Li et al. [104]	McMaster University	Canada	IMU	4
	Ju (init.) et al. [105]	Seoul National University	South Korea	Foot-mounted IMU	5
	Kikutchi et al. [106]	Iwate University	Japan	Direction of departure-based BLE localization	8
	Su et al. [107]	National Taiwan University of Science and Technology	Taiwan	Wi-Fi + magnetic + IMU fingerprinting	9
	Ben-Moshe et al. [108]	Ariel University	Israel	Camera and range sensing	14
	Sadhu et al. [109]	Rutgers University	United States	Wi-Fi fingerprinting	15
	Guimarães et al. [39]	Fraunhofer Research Institute	Portugal	Wi-Fi + magnetic + IMU fingerprinting	16

wireless signal travels is known, the distance between the two devices can be easily extracted.

Alternatively, time difference of flight (TDoF) techniques can be used to estimate the distance between the devices. One of the devices can transmit two signals of different types at the same time (i.e., an ultrasound signal and an RF signal). Observe that these two signals travel at different speeds; RF travels at the speed of light, while ultrasound signals travel at the speed of sound. The receiving device can timestamp when these signals are received, and it can then use the equation in Figure 2 to estimate the distance between the Tx and Rx.

In some cases, the distance between two devices can be measured using a third transmitting device, as shown in Figure 2. Instead of measuring the TDoF, we can now measure the TDoA of two wireless transmissions. Device Tx(1) in Figure 2 makes a single wireless transmission. As soon as device Tx(2) receives the transmission from device Tx(1), it initiates its own transmission. Device Rx timestamps the reception of both transmissions and computes the distance between devices Tx(1) and Tx(2) according to the equation in Figure 2.

Wireless mediums for ranging

The type of signals used for the transmissions shown in Figure 2 is critical. The most popular wireless signals for ranging are RF and sound/ultrasound signals. RF signals have excellent penetration characteristics, which make them ideal for indoor localization scenarios. In addition, there is already widely deployed RF infrastructure, such as Wi-Fi access points, that can be leveraged for localization purposes. On the negative side, RF signals travel at the speed of light, which makes accurate timestamping a challenging problem to solve. Inaccurate timestamps can lead to large ranging errors and, therefore, to poor localization accuracy.

Sound and ultrasound signals [26], [27] have the advantage of lower propagation speed over RF signals. The lower the propagation speed of the wireless transmission, the easier it is to design the necessary hardware for accurately timestamping these transmissions. On the negative side, sound and ultrasound signals require line of sight, as they do not penetrate materials like walls. In addition, this type of signal can interfere with hearing, as they are audible by humans (sound signals) and animals (ultrasound signals).

More recently, UWB signals [40] have become increasingly popular for indoor localization applications. UWB signals are unique, as they consist of very narrow pulses transmitted over a large bandwidth, usually in the order of gighertz. Even though they overlap with multiple frequencies, no interference is created, as the transmission power at each frequency is very low. UWB transmissions require the Tx and Rx to be coordinated to send and receive pulses. The advantage of UWB transmissions in indoor localization applications lies in their ability to very accurately timestamp the wireless transmissions. Conventional RF signals reflect in indoor environment structures, resulting in distortions to the direct path signal, which in turn makes accurate timestamping challenging. In the case of UWB (Figure 2), the narrower, but higher bandwidth, pulses can still be reflected by the indoor environment structures. However, because of the pulses being very narrow, it is now easier to differentiate the direct path pulse from the reflected ones. As a result, UWB signals can measure distances with accuracies as low as a few centimeters.

Competition evaluation process

The competition is a two-day event. During the first day, all teams are given 7 h to set up their indoor location technologies in the evaluation area. During this time, teams are able to deploy their custom hardware, if any, and also perform any profiling of the space necessary (i.e., fingerprinting, map construction, and so forth). Each team that requires implementation its own custom hardware is allowed to deploy up to a predetermined (usually ten) maximum number of devices (i.e., access points, custom RF modules, magnetic field modulators, light-modulating lamps, and so on) depending on the size of the evaluation area.

At the beginning of the first day, the organizers indicate an origin point for the reference coordinate system that each team should use to report locations. Locations are reported as two-dimensional (2-D) or three-dimensional (3-D) coordinates [i.e., (2.12 m, 5.1 m)] with respect to this origin point.

At the end of the first day, the deployed hardware from all teams is turned off, and all contestants leave the evaluation area. At that time, the organizers mark 20 points on the floor of the evaluation area and measure the *x*, *y*, and *z* coordinates of these points with respect to the predefined origin point. The ground truth measurements of the evaluation points are taken either using laser range finders or more advanced 3-D laser scanners, providing centimeter-level or even millimeter-level accuracy.

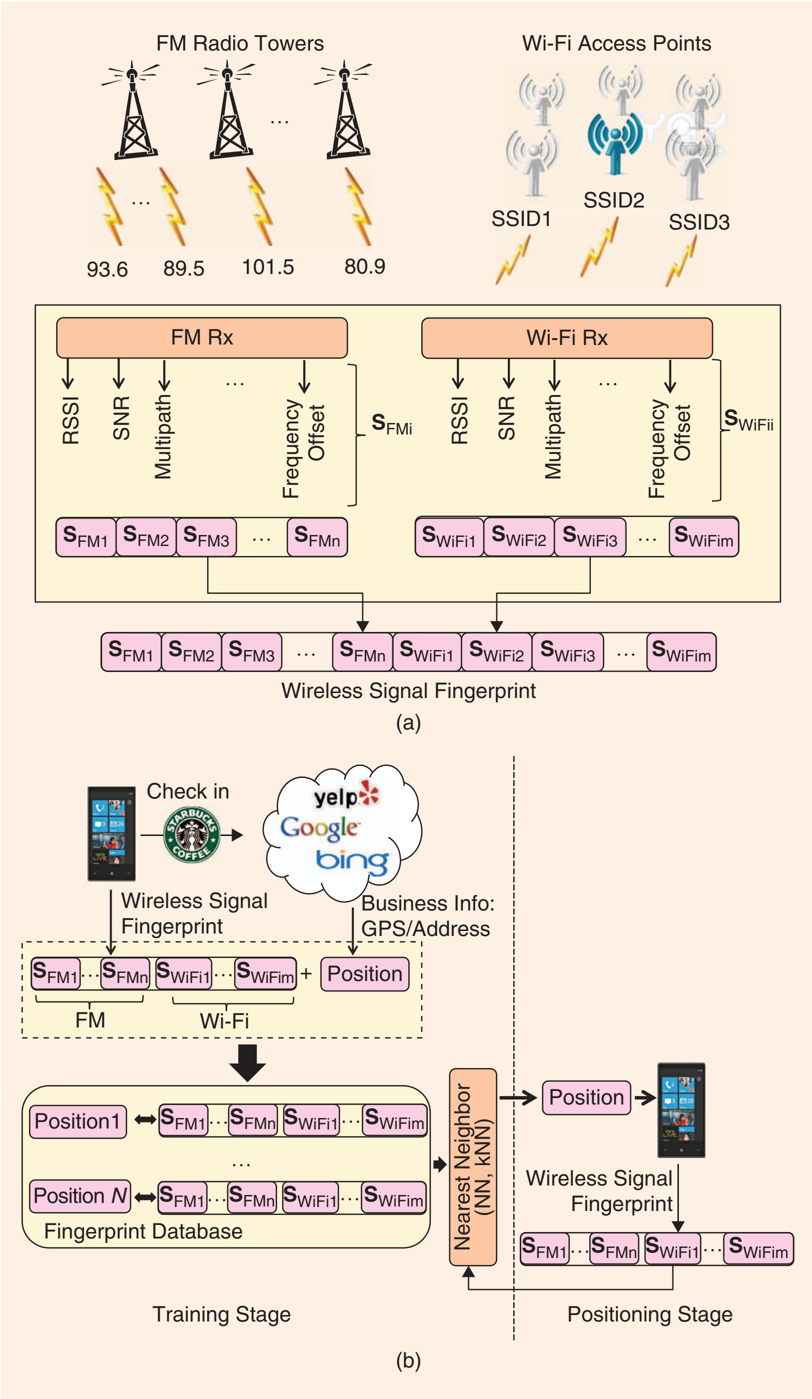

FIGURE 1. An overview of wireless fingerprinting. (a) Creating a wireless fingerprint and (b) localization using wireless fingerprinting. SSID: service set identifier.

During the second day of the evaluation, each team shows up at a preassigned time slot, turns on its deployed system, and hands the device over to the organizers to be localized. The device can be a mobile phone, a tablet, or a laptop depending on the system under test. The organizers carry the device above each of the 20 evaluation points, wait for a couple of seconds, and record the location reported by the system under test. All systems are evaluated based on the average location error across all 20 evaluation points. The location error for a given point is defined as the Euclidean distance between the true and reported coordinates for that point. Even though we recorded location estimates only on the premeasured 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.

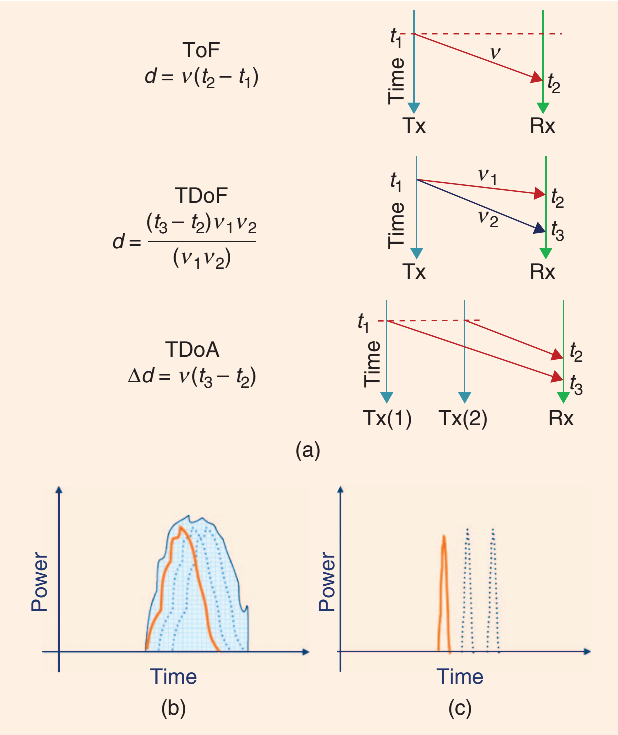

FIGURE 2. The ranging techniques for indoor localization and the advantage of UWB pulses. (a) The ranging primitives and (b) the normal RF pulses versus (c) the narrow RF pulses.

Note that when evaluating a team, the organizers visit the evaluation points in sequence (start with evaluation point one, and end with evaluation point 20). However, the moving path is not predetermined. A different path and moving pattern can be taken every time. Also, the competition area is open to people during the actual evaluation of the teams. For the most part, many people walk around the evaluation area or closely observe the evaluation process of each system.

Variations across competitions

The competition is colocated with the Association for Computing Machinery/IEEE International Conference on Information Processing in Sensor Networks. As a result, the evaluation area used each year depends on the available space at the conference venue and the country where the conference takes place. Because of this, the evaluation area varies every year.

Figure 3 shows the evaluation areas and the evaluation points used in the last four competitions. In 2014, a relatively small area of 300 m^2, consisting of two rooms and a hallway, was used. In 2015, a large 2,000-m^2 open-space area that featured only two rooms was used. In 2016, the evaluation area included a single open-space area of approximately 465 m^2. In 2017, a 600-m^2 area spanning two floors with a large atrium and 18-ft tall stairs/escalators was used as the evaluation area.

All teams were required to report 2-D locations for each evaluation point. The only exceptions were the teams in the

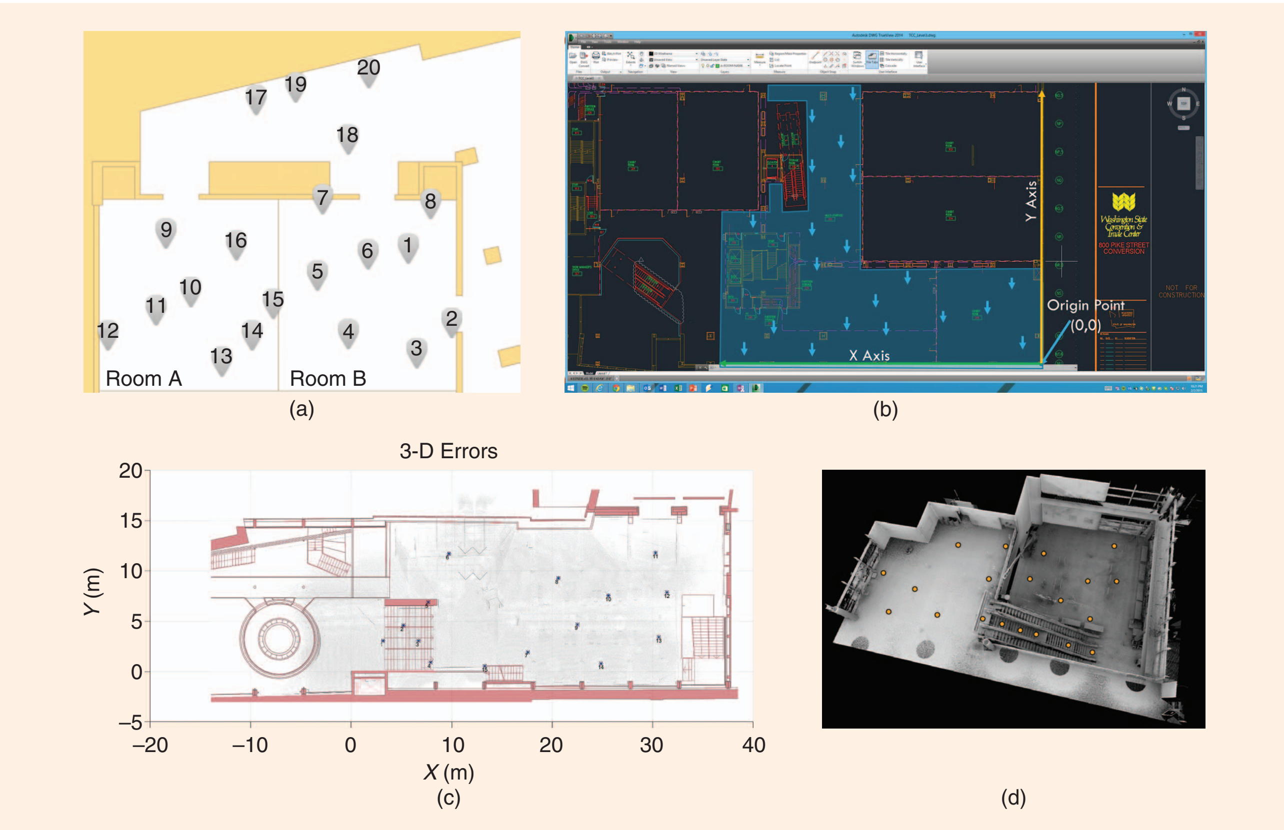

FIGURE 3. The different evaluation areas used in the last four Microsoft Indoor Localization Competitions. The evaluation points are also shown: (a) 2014 in Berlin, Germany (300 m^2); (b) 2015 in Seattle, Washington (2,000 m^2); (c) 2016 in Vienna, Austria (465 m^2); and (d) 2017 in Pittsburgh, Pennsylvania (600 m^2).

infrastructure-based category at the 2016 and 2017 competitions. These teams were required to report 3-D locations.

Teams that relied on Wi-Fi were only allowed to leverage the existing deployed networking infrastucture at the conference venue. In 2015, there were four Wi-Fi access points, and in 2016, three Wi-Fi access points. The only exception to this rule was the 2014 competition, where the teams were able to use ten Wi-Fi access points that were deployed by the organizers.

Note that the deployment of ten dedicated Wi-Fi 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 ten access points resulted into an unusually high density of access points. Most areas today (i.e., malls) provide fewer numbers of access points that are also mounted differently in the space (i.e., mounted on the ceiling).

Participating teams

All teams were classified into two categories: infrastructure-free and infrastructure-based, according to 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 Wi-Fi infrastructure. Most of these approaches leverage existing Wi-Fi signals and combine them with sensors, such as accelerometer, gyro, and compass, on existing commercially available devices, such as phones and tablets. However, teams in the infrastructure-based category required the deployment of custom hardware, such as Bluetooth beacons, magnetic resonators, ultrasound speakers, custom RF Tx, and more.

Tables 1 and 2 provide an overview of all the teams that participated in the past four competitions (also see Figure 4). The technology used by each team and the team's global rank in terms of accuracy for that year are also listed.

Localization accuracy overview

Figure 5 shows the average localization error of every team that was successfully evaluated in the last four years of the competition. Looking across all years and types of systems, lidar-based technology seems to consistently achieve the lowest localization error (Sánchez et al. in 2015 with 0.2 m, Leica and also Zhang et al. in 2016 with 0.05 m and 0.16 m, respectively, and Zhang et al. in 2017 with 0.03 m). Even though extremely accurate, the cost as well as the size and power requirements of lidar sensors prevents this technology from becoming a mainstream indoor location solution. In fact, this type of sensor was accepted as exhibition systems, as the main motivation behind the competition was to focus on technologies that can be massively deployed in the near future to enable everyday devices, such as phones and tablets, to be accurately localized indoors.

Infrastructure-free technologies

With this in mind, infrastructure-free approaches seem ideal, as they don't require any hardware to be deployed. They solely rely on Wi-Fi/magnetic fingerprints and the inertial sensors already available on most phones and tablets. The best teams in this category were able to achieve localization accuracy anywhere between 1.1 and 1.9 m. In 2014, Beder and Klepal and Li et al. achieved 1.56 and 1.96-m errors, respectively, but in a relatively small area with an unusually high density of Wi-Fi access points (ten Wi-Fi access points were deployed in 2014, as described in the "Variations Across Competitions" section). In 2015, SPIRIT Navigation and Guimarães et al. were able to achieve 1.9 m and 2.6 m, respectively, but in a much larger open-space evaluation area with only three Wi-Fi access points. Guimarães et al. also competed in 2016, achieving a localization error of 1.1 m, the lowest error across all teams leveraging similar technology.

Surprisingly, the accuracy of infrastructure-free teams in the 2017 competition decreased drastically. Even teams that had performed very well in 2015 and 2016 were not able to get anywhere close to 1–2-m accuracy (i.e., the team from Portugal's Fraunhofer Research Institute). Most of the teams in this category attributed this discrepancy to three factors. First, they observed that the Wi-Fi fingerprints in the evaluation area were fluctuating significantly over time, more than in any other location they had previously tested their systems. Second, the magnetic fingerprints were completely unreliable, most probably because of the 18-ft-tall escalators that were operating during both days of the competition. Third, five of the total 20 evaluation points were placed on the stairs in between the escalators, resulting in more than usual localization error for this type of system.

The only systems that performed very well in this category in 2017 did not rely on Wi-Fi and/or magnetic fingerprinting. Instead, they depended on either the phone's sensors (Li et al.) or on foot-mounted IMU sensors (Ju et al.).

When considering a realistic environment, such as a shopping mall or an office building, infrastructure-free technologies can achieve accuracies of approximately 2 m. However, these results do not take into account the temporal variations of the wireless signal fingerprints. During the competition, teams train their systems one day before the evaluation, resulting in a positively biased evaluation. When considering temporal variations, we expect the localization error to increase by 1 or 2 m, resulting into an expected error of 3–4 m.

Another interesting observation is that even though most of the infrastructure-free teams rely on the same signals and sensors, the actual localization accuracy can vary widely. For instance, in 2014, the localization error of the Wi-Fi-based approaches ranged anywhere between 1.56 and 5.23 m, with similar trends in 2015 and 2016. Even though Wi-Fi fingerprinting is a very-well-studied topic, the exact implementation can significantly affect the localization accuracy.

Infrastructure-based technologies

When considering infrastructure-based approaches, there is a much more diverse set of technologies on which both academia and industry have focused. Most of the systems that have been evaluated so far focus on six core technologies: sound/ultrasound ToF, UWB, visible light communication, BLE beacons, magnetic resonators, and 2.4-GHz phase offset.

Across all of these technologies, UWB seems to rapidly rise as the most accurate and popular infrastructure-based indoor

FIGURE 4. An example of participating teams during set-up and evaluation days from the 2014–2016 Microsoft Indoor Localization Competitions: (a) a set-up day in 2016, (b) sound-based localization in 2016 [41], (c) a system evaluation in 2014, (d) magnetic resonators [42], (e) a system evaluation in 2014 [43], (f) a system evaluation in 2014 [42], (g) a 24-GHz radar [44], (h) a lidar system [45], (i) a Leica backpack [46], (j) visible light [47], (k) sound-based localization [27], (l) a UWB transceiver, (m) a UWB radar [48], (n) a UWB system [49], and (o) sound-based localization in 2016 [50].

location technology. In 2014, no UWB systems were evaluated. In 2015, three systems based on UWB were evaluated, including one from Time Domain, one of the pioneers of UWB technology. In 2016, eight teams leveraged UWB technology. These teams were able to achieve impressive accuracies ranging from 0.39 m in 2014 (2-D location error by Time Domain) to 0.17 m in 2017 (3-D location error by Quantitec). The majority of the competing UWB-based systems were able to easily achieve submeter localization accuracy. Surprisingly, all of these systems were built on the same UWB radio transceiver by Decawave [40]. The major differences

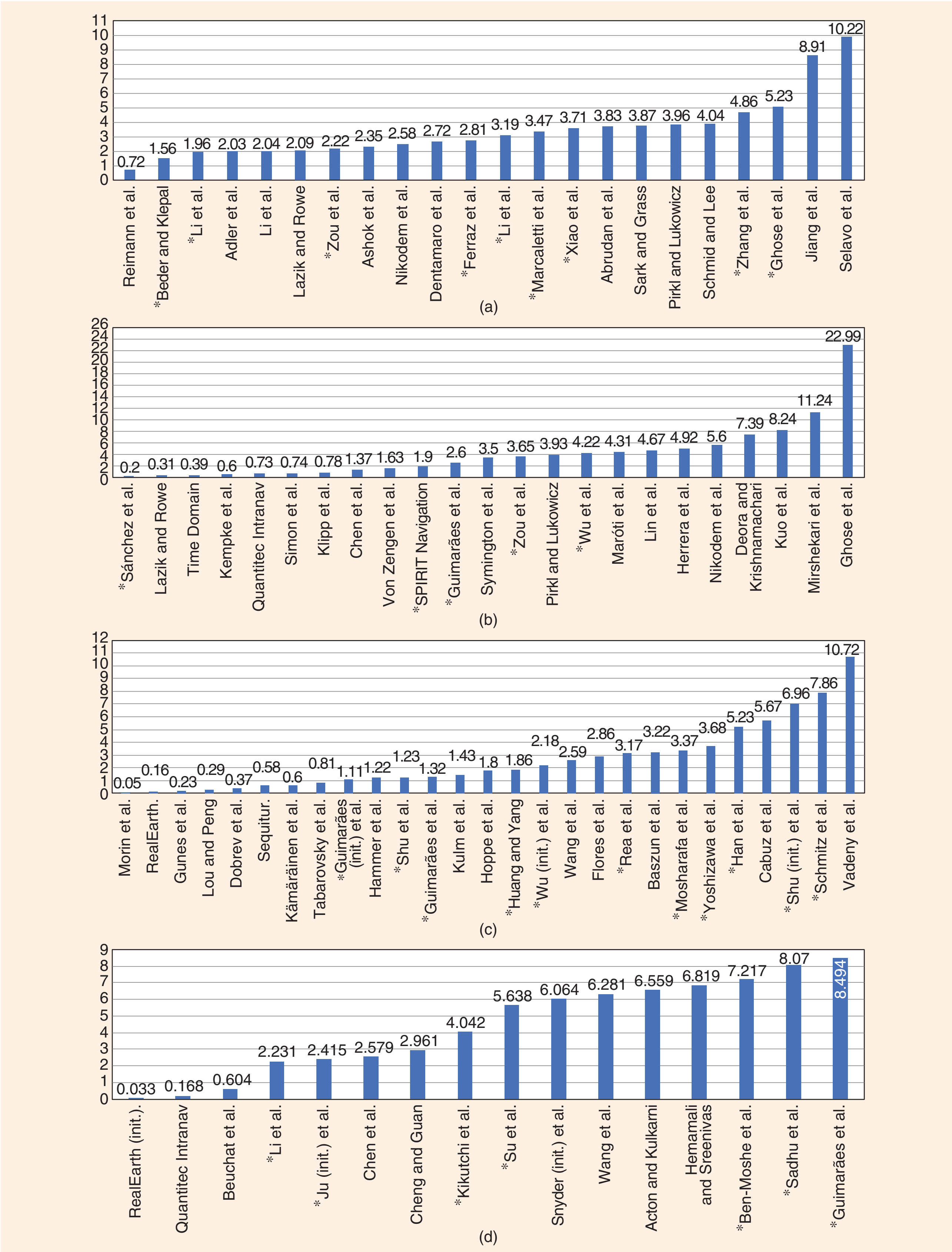

FIGURE 5. The average localization error for all competing teams grouped by year. Teams with an * are infrastructure-free teams. Teams with (init.) had to bootstrap their systems at a known location inside the evaluation area. Tables 1 and 2 provide more details about each team. As a reference, if a team were to always report the center of the evaluation area as the true location, the average location error would be 7, 16, and 9 m for the 2014, 2015, and 2016 competitions, respectively. Data for (a) 2014, (b) 2015, (c) 2016, and (d) 2017.

across these systems were the design of the transceiver's antenna and the algorithms used for filtering non-line-of-sight signals.

Interestingly, and similarly to Wi-Fi-based technologies, there is a significant variation in the performance of UWB-based solutions. Even though all teams leverage the exact same transceiver, localization accuracy ranges anywhere between 0.23 and 3.22 m for this type of system. This variation underlines the importance of properly designing the antenna front end and the ability to effectively handle non-line-of-sight signals during the location computation.

Technologies based on the ToF of acoustic signals were able to realize comparable accuracy to UWB-based systems. In particular, Lazik and Rowe in 2015 were able to attain an error of 0.31 m, a significant improvement compared to the error of 2.09 m that the same team achieved in the 2014 competition. The error reached by other systems based on similar technology was much higher, ranging from 1.2 m (Hammer et al.) all the way to 2.86 m (Flores et al.) in 2016.

Measuring the phase offset of Wi-Fi signals has been getting increasingly popular in the academic community. During the competition, we were able to evaluate three such implementations (Reimann et al. and Schmid and Lee in 2014, and Symington et al. in 2015). All of these systems require customized hardware to enable high-resolution phase measurements. The implementation from Reimann et al. has been by the far the most accurate, reaching an error of 0.72 m. More interestingly, Reimann et al. only deployed six out of the maximum number of ten anchors allowed. This was also the system with the best performance during the 2014 competition. It was surpassed in accuracy by only the ultrasound system by Lazik and Rowe, most UWB-based solutions, and lidar-based systems.

Bluetooth beacons are one of the easiest ways to deploy an indoor location solution but one of the hardest ones to accomplish fine-grain accuracy. Even though only a few such systems were evaluated in this competition, the system by Chen et al. in 2015 accomplished an impressive localization error of only 1.37 m. This system was using PDR along with BLE beacons, and even though not as accurate as UWB or ultrasound technologies, the achieved accuracy is impressive given the large evaluation area in the 2015 competition. As a comparison, Dentamaro et al. in 2014 attained a 2.72-m error using Wi-Fi fingerprinting and BLE beacons in a much smaller space with a very high density of Wi-Fi access points.

Lab versus reality

Indoor localization approaches are usually evaluated in highly controlled environments (i.e., a research lab). This type of evaluation could positively bias the performance of the system. During the 2014 competition, we attempted to quantify this bias. In particular, we asked each participating team to report the localization error that it had previously attained in its own experiments, and we compared this error to the one achieved in the competition. Most teams had worse accuracy by approximately 1.5–4 m. From the infrastructure-based teams, only Reimann et al. achieved the same error as the one reported in their own experiments. Infrastructure-free teams mainly accomplished the same or, in a few cases (Beder and Klepal, Li et al.), better performance compared to their own experimental evaluation. We believe that this was due to the large number of Wi-Fi access points that were leveraged in the evaluation study. Given that the evaluation area was relatively small (300 m^2), all ten access points could be successfully sniffed from every location in the evaluation area, creating an ideal setup for Wi-Fi-based approaches.

Impact of furniture setup on accuracy

Furthermore, we leveraged the two rooms in the 2014 evaluation area to quantify the impact of furniture setup on the accuracy of the systems. Even though both rooms had furniture, we purposely changed the furniture setup in only one of these rooms after the teams had calibrated their systems. By comparing the accuracy achieved by the systems in these two rooms, we were able to quantify the impact of the furniture setup on the localization accuracy.

With the exception of Li et al., the rest of the infrastructure-free approaches reported higher location errors in the room where the furniture setup was modified. The error increase varied anywhere between 0.47 and 0.94 m. Surprisingly, even infrastructure-based approaches seem to be affected by the changes in the furniture setup. The top four teams in this category, with the exception of Adler et al., exhibited an increase in location errors in the modified room that varied anywhere between 0.11 and 2.99 m.

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 field, 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.

Accuracy versus cost

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 UWB and ultrasound approaches can comfortably achieve localization accuracy well below 0.5 m, their deployment overhead remains high. Custom hardware needs to be carefully deployed in every area where indoor location services are needed. Given that this hardware needs to be hardwired to power to facilitate maintenance over time, this increases the cost and effort required to deploy accurate indoor location solutions.

However, fingerprinting-based approaches might not require the deployment of custom hardware, but they rely on laborious, manual data collection processes. Even worse, fingerprinting is a tedious process that needs to be frequently repeated to ensure that the localization accuracy is resilient to temporal signal variations and environmental changes, such as furniture setup and human motion. Furthermore, even under somewhat ideal conditions, fingerprinting-based approaches are not able to provide localization accuracy below 2 m, making these technologies unsuitable for a variety of applications that require submeter accuracy.

From directly observing all the teams during the set-up day, it became clear that the installation/profiling cost of current approaches is prohibitively high. All teams were given 7 h to deploy their hardware and/or profile a relatively small area of a building. Even though one would think that 7 h should be way more than enough time for the teams to set up their systems, this wasn't the case. On average, it took each team 5 h to set up its approach in the designated evaluation area, with many teams leveraging the full 7 h of set-up time. For a couple of teams, 7 h was not enough time to fully position their systems. This is particularly concerning given the fact that the teams did not have to worry about any practical issues that any commercial installation would impose (i.e., aesthetics, properly hiding the deployed equipment, and so forth). In addition, the whole process of installing 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 positioning 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.

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, root-mean-square error, 95th percentile, and so on), there are variations in the real world that are not being properly captured by these metrics. For instance, 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.

The design of appropriate evaluation metrics can have a significant impact on the results of the competition and the conclusions that are made. In particular, there is an opportunity for researchers to contribute to future competitions (and to the research community in general) by developing metrics that are fair across a set of competitors that participate using a heterogeneous set of platforms and technologies.

Designing a better indoor localization competition

Organizing an indoor localization competition over the past four years gave us a great deal 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, instead of using relatively small evaluation areas consisting of a few 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.

Third, 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.

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

Fifth, 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, set-up time, and more, should be quantified in detail.

Conclusions

The Microsoft Indoor Localization Competition described in this article 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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