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Indoor Localization with Smartphones

Harnessing the sensor suite in your pocket.

The need for indoor localization systems that can provide reliable access to location information in areas that are not serviced sufficiently by a global positioning system (GPS) has continued to grow. There are a wide variety of use cases for this localization data and increasing interest from industry, academia, and government agencies that has fueled research in this area. Smartphones are uniquely positioned to be a critical part of a localization solution based on the proliferation of these devices and the diverse array of sensors and radios that they contain. In this article, the capabilities of these sensors are explored along with the benefits and drawbacks of each for

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localization. Various methods for employing these sensors are surveyed. Many localization systems currently being explored utilize a combination of complimentary methods to enhance accuracy and reliability and decrease energy consumption of the overall system. Several of these localization frameworks are also explored. Finally, we describe the major challenges that are being faced in current research on indoor localization with smartphones, as they are critical for charting the path for future advances in indoor localization.

THE NEED FOR INDOOR LOCALIZATION

Global navigation satellite systems (GNSSs) have transformed the way that people navigate, travel, automate, and gather information about the world around them. Indoor localization systems have the potential to similarly change how people function in locations where satellite-based localization systems are rendered ineffective. There is a need for systems that can bridge this gap and create continuity in localization regardless of location.

Indoor localization is a challenging problem, particularly in complex spaces such as shopping malls, schools, high-rise buildings, hospitals, subways, tunnels, and mines. The variety of locales involve differing ambient environments, obstructions, architectures, and materials, which makes accurate localization difficult. There are also challenges associated with the movement of people, machinery, furniture, and equipment, which cause variations and interferences. There are many different approaches to localizing indoors, but, unfortunately, there is currently no definitive standard to meet all the needs and challenges for localization in every indoor environment.

The ability to track people and equipment indoors has applications in many areas (Figure 1). Factory and warehouse automation through asset tracking and optimization analysis can serve to increase productivity by effectively scheduling resources and equipment. Hospitals can track patients, employees, and equipment to enhance navigation and allow for the automation of hospital information systems. Retail stores can use beacons to announce sales, customize displays to the shopper, collect shopping pattern data, and assist customers in finding products. Parking garages and underground parking structures could track their fill capacity, direct vehicles to open spots, locate vehicles, and ultimately enhance autonomous vehicle routing [37].

Companies such as Aisle411 have already begun to deploy indoor localization for floor-plan optimization and augmented reality in retail locations. Disney uses a wristband on guests called the *MagicBand* that integrates with its theme park–wide MyMagicPlus system to create a customized experience for visitors as they are tracked throughout the park, including indoor locales. The American National Football League has partnered with Zebra to track players on the field during

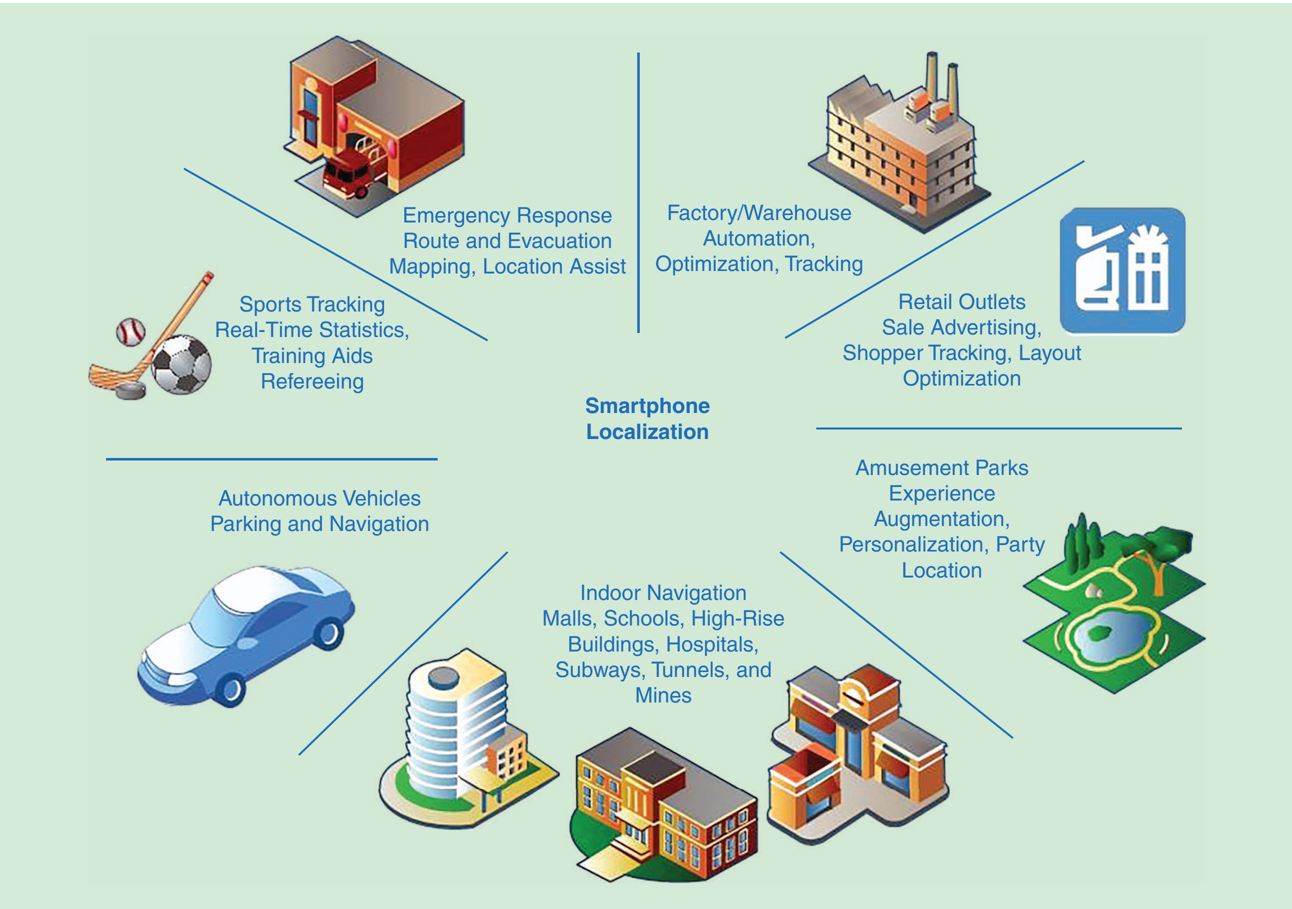

FIGURE 1. Some use cases for smartphone indoor localization.

The ability to track people and equipment indoors has applications in many areas.

games to enhance sports officiating as well as to augment the experience for fans. The ability to track people in stadiums, in addition to helping to find family or friends in a crowd, is also useful for emergency responders in the case of a disaster.

Realizing the importance and potential of indoor localization, the International Conference on Indoor Positioning and Indoor Navigation has been held since 2010 to bring researchers, developers, and service providers together to share research and compete in challenges. Major corporations have expressed interest in furthering the cause of indoor localization. The Microsoft Indoor Localization Competition was started in 2014 and encourages competition among teams in various challenges to spur research in the area. Similarly, beginning in 2017, the National Institute of Standards and Technology also created its own indoor localization competition (Performance Evaluation of Smartphone Indoor Localization) [1] to encourage the development of the best possible indoor localization solutions.

In 2015, the U.S. Federal Communications Commission announced a mandate for the update of the Enhanced 911 standards to include a requirement for all commercial mobile radio service providers to supply enhanced location data for 40% of all wireless 911 calls by 2017. This enhanced location data requires *x*/*y* location within 50 m. In addition, the mandate requires *z*-axis data for handsets with barometric sensor data by 2018. These additional requirements are an incremental step toward the use of improved indoor localization by emergency responders.

As smartphones are the most widely adopted piece of personal communication technology today [36], they possess a unique advantage to assist with indoor localization. These devices have the requisite sensors to facilitate localization in myriad ways. As smartphones continue to evolve, future iterations are likely to continue to improve upon this sensor suite. In this article, we survey the current state of indoor localization research and practices that utilize commodity consumer smartphone technology.

SMARTPHONE: SENSORS AND RADIOS

Today's smartphones have an arsenal of sensors and radios (Figure 2) that can provide valuable data to enable indoor localization through a number of different methods. As many people carry their smartphones with them everywhere they go, it is a compelling technology for enabling localization and navigation in these scenarios.

INTERFACES

The microelectromechanical-system-based accelerometers, gyroscopes, and magnetometers in today's smartphones provide motion and orientation data. The accelerometer detects relative motion of the device in the form of acceleration. As the calculation of distance traveled is the double-integral of the acceleration, small acceleration errors can rapidly accumulate as large positional errors. The gyroscope provides angular acceleration data relative to the body frame of the device. This angular acceleration data can be used to derive Euler angles or pitch, roll, and yaw, which express angular position relative to the body frame. In the same way that the accelerometer accumulates distance errors, the gyroscope can rapidly accumulate angular position errors. A way to overcome this error is to periodically recalibrate angular position based on magnetometer data. The magnetometer detects angular position data of the body of the device relative to magnetic north. Other sources of magnetic fields such as electronics, metals, and magnets can introduce errors. The combination of accelerometer and gyroscope data is often known as six-degrees-of-freedom (6 DoF) data and provides a characterization of the motion and orientation of the smartphone as relative data without another frame of reference. The inclusion of magnetometer data is known as 9 DoF and provides a frame of reference by anchoring this data relative to magnetic north.

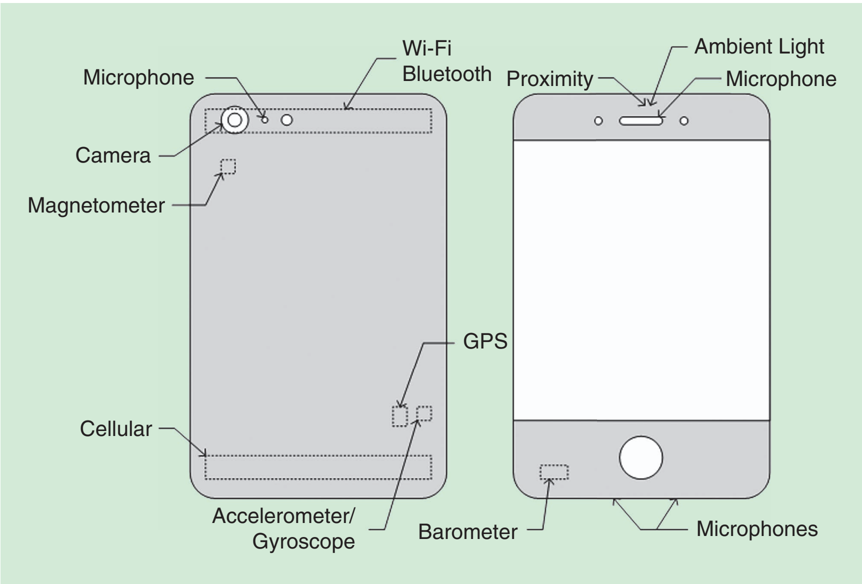

FIGURE 2. Smartphone sensors and radios.

CELLULAR RADIO

As cellular radios in smartphones (third and fourth generation/long-term evolution) are designed for long-range communication, these signals are often available as a source of positioning indoors with respect to a cellular base station. However, because of interference and multipath effects indoors, the received signal strength indicator (RSSI) for wireless cellular signals often varies greatly. Also, even though cellular signals have a relatively high range, the low deployment density of cellular base stations means that the localization accuracy with these signals is not very high, varying between 50 and 100 m.

WI-FI RADIO

Wi-Fi radios work with wireless signals that are shorter range than cellular but longer range than Bluetooth. Wi-Fi access points can be used as beacons, and, because of their proliferation in indoor locales, they are being used more and more as sources for indoor localization data by analyzing signal strength (using an RSSI). IEEE Standard 802.11-2016 [38] recently introduced a fine-timing measurement protocol called *Wi-Fi location* that includes a measurement of the time it takes for the Wi-Fi signal to travel, enabling distance measurement. However, no Wi-Fi location-certified smartphones have reached the market yet.

BLUETOOTH AND BLUETOOTH LOW-ENERGY RADIOS

Bluetooth devices or beacons can also be used as point sources for localization. Bluetooth radios are lower range than cellular and Wi-Fi radios. Bluetooth low energy (BLE) is a lower bandwidth and lower power protocol than Bluetooth that works by using a lower transmit duty cycle than Bluetooth classic, and it is better suited for applications that do not require high data rates. It is anticipated that by 2018, 90% of smartphones will support BLE. A subset of BLE known as *Apple iBeacon* advertises and allows background applications in an internetwork operating system to be alerted when in proximity of a beacon. The same challenges with RSSI detection that adhere to cellular/Wi-Fi radios also apply to Bluetooth radios.

CAMERA

Today's smartphones have sophisticated high-resolution cameras that can be used to detect identifying features indoors or aid in the detection of relative motion. To utilize this sensor, the camera needs to be exposed. Typical smartphone front-facing cameras are lower resolution and face the user. The rear-facing cameras usually have a higher image resolution or even dual cameras. However, image processing requires high computational overhead in comparison to some of the other sensors and has variable performance in low light conditions.

BAROMETER

The barometer detects barometric pressure and is primarily used in localization systems as a relative indicator of vertical elevation (z-axis localization). Data from this sensor is especially useful to eliminate the vertical positional drift from purely inertial localization techniques. For example, in the case of using elevators, an inertial solution utilizing step detection may be a complete failure [2]. Unfortunately, wind, indoor ventilation systems, and weather fluctuations can cause changes in the barometric pressure and are potential sources of error during vertical localization. Also, barometric sensors are not as readily available in all smartphones.

GPS

The GPS sensors in smartphones are the de facto standard for outdoor localization, but they perform poorly or not at all in indoor conditions where they lose line-of-sight to the GPS satellite constellation. They can still be used in some indoor scenarios near windows or outside doors or while entering buildings to calibrate an indoor localization framework.

MICROPHONES

Smartphones contain one or more microphones that can be used to detect ambient sound sources or beacons that may be used for localization. As these microphones are optimized for speech, they are not necessarily optimized for detection of sound outside of the audible range. Microphones can also be adversely affected if the phone is carried in a pocket or bag.

PROXIMITY SENSORS

The proximity sensors in smartphones typically utilize an infrared light-emitting diode (LED) and detector or capacitive proximity sensors. The primary use for these sensors is to detect the presence of the hand or face near the smartphone. The limited range on these sensors renders them ineffective for most localization scenarios.

AMBIENT-LIGHT SENSOR

An ambient-light sensor detects the magnitude of ambient light. The typical use for this sensor is brightness adjustment on the smartphone for different ambient-light scenarios. The use of this sensor for localization can be challenging, as natural ambient light in a building is highly dependent on the time of day. However, artificial lighting fixtures/sources can be employed to overcome these challenges. Recent works have successfully incorporated ambient-light sensors for indoor localization.

TEMPERATURE SENSORS

Changes in temperature in different indoor locales can also be measured and used for indoor localization. But the usefulness of temperature sensors on smartphones for localization is practically limited, as they can be affected by device and user body temperature.

EXTERNAL SENSORS AND RADIOS

The addition of external sensors to the smartphone's sensor suite can also aid in localization by adding capabilities that are not otherwise available in the phone itself. External sensors can either be attached via external ports on the smartphone or wirelessly interface with the smartphone using Bluetooth, BLE, and/or Wi-Fi. Some examples of promising external sensors for localization include ultrawideband radios that can be used for time-of-flight (ToF) ranging with beacons and ultrasonic sensors that can similarly use sound waves. The radio-frequency (RF) identification doorway and threshold sensors can indicate proximity to these points and estimate movement around an indoor environment. These external sensors add to the cost and complexity of the indoor localization system.

INDOOR LOCALIZATION METHODS

Several methods have been explored for indoor localization with smartphones in recent years. These methods utilize the sensors and radios discussed in the "Smartphone: Sensors and Radios" section. Some major indoor localization techniques are shown in Figure 3, and a summary of indoor localization techniques can be found in Table 1.

DEAD RECKONING

Dead reckoning refers to the class of techniques in which sensor data is used along with the previously known position

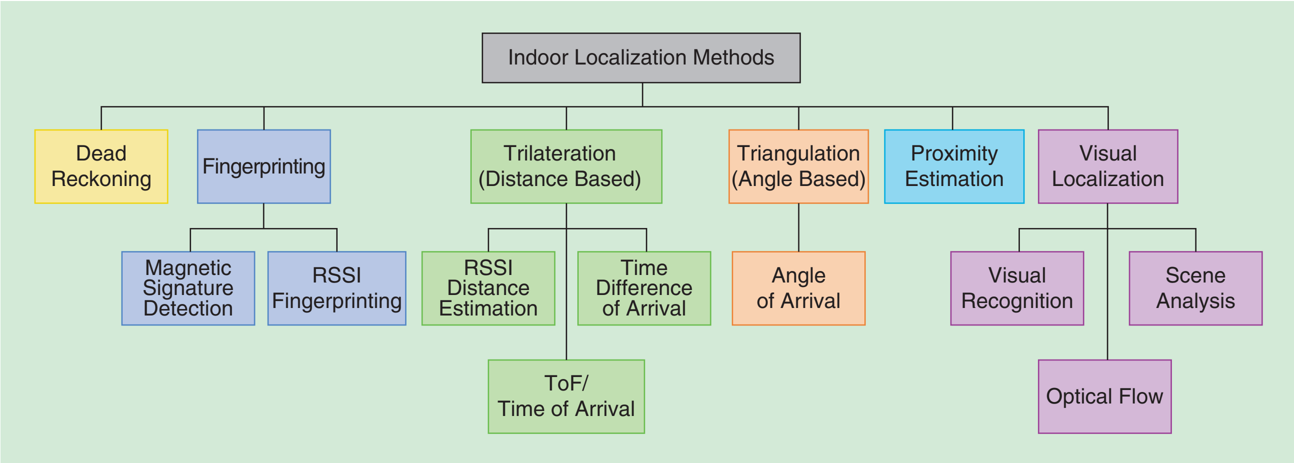

FIGURE 3. A taxonomy of indoor localization methods.

Table 1. A summary of indoor localization methods.

Authors	Technology	Technique	Accuracy
Pasricha et al. [27]	A, G, Wi-Fi,	PDR + fingerprinting: KNN, NN	Mean error 1 m
Bitsch et al. [3]	A, G, M	PDR, MM	Mean error 1.6 m
Kim et al. [5]	A, G, M	Motion of pelvis as inverted pendulum for stride length	1% step, 5% distance, 5% heading errors
Bahl and Padmanabhan [10]	Wi-Fi	RSSI fingerprinting and Euclidean distance measure empirical calculation	Mean error 20.5 m
LaMarca et al. [12]	Wi-Fi, cellular	Fingerprinting	Mean error 20 m
Chintalapudi et al. [13]	Wi-Fi	RSSI distance estimation: EZ algorithm	Median error 2 m
Karalar and Rabaey [14]	RF	ToF	Error within 2.5 m
Höflinger et al. [16]	Acoustic	Time difference of arrival (TDoA)	Mean error 30 cm
Xiong and Jamieson [17]	RF	Angle of arrival (AoA)	Median accuracy 23 cm
Bitsch et al. [21]	Camera	Optical flow of ground	Mean error 3 m
Beauregard et al. [22]	A, G, M	PDR ZUPT, particle filter	Mean error 2.56 m
Hellmers et al. [24]	Magnetic coil, A, G, M	ToF, EKF, PDR	Deviation of 0.15–0.3 m
Martin et al. [30]	Mic, photosensor, camera, A, G, Wi-Fi	Fingerprinting	87% accuracy
Lazik et al. [31]	Ultrasound, BLE	TDoA	Error: three dimensional: 16.1 cm; two dimensional: 19.8 cm
Xu et al. [32]	A, G, M, photosensor	Illumination peak detection, PDR, MM	Mean error 0.38–0.74 m

A: accelerometer; G: gyroscope; M: magnetometer; PDR: pedestrian dead reckoning; MM: map matching; KNN: k-nearest neighbor; NN: neural networks; ZUPT: zero velocity update; EKF: extended Kalman filter.

to determine the current position. The most commonly used strategy in this area is known as *pedometer-based dead reckoning*. This strategy works by first detecting and then counting steps and using this data with stride length information to estimate distance traveled. Figure 4 shows a simplistic strategy for step detection in FootPath (indoor navigation) [3]. Steps can be detected if there is a difference in acceleration p on the low-pass filter in the vertical direction in a given time window. In [4], stride length is modeled to have a linear relationship with step frequency, whereas [5] models the motion of the pelvis as an inverted pendulum to approximate stride length. A heading (direction) estimation is achieved with magnetometers and horizontal acceleration data. The step count, along with stride length and heading estimate combine to form a movement vector. This movement vector can be applied to a previous location to approximate the current location. The motion sensors found in smartphones (the accelerometer, gyroscope, and magnetometer) are capable of high sampling and update rates and allow such pedometer dead reckoning [6], [7]. The pedometer-based approach has its challenges; e.g., distance calculations can accumulate errors because of an imperfect stride length estimation or irregular walking pattern. This approach is also ineffective for alternate means of transportation that do not require a step motion such as wheelchairs, moving walkways, and subway trains, among others.

FINGERPRINTING

Fingerprinting involves characterizing an environment based on parametric data from one or more wireless radios or sensors over many spatial points. This process involves a survey step in which locations are characterized with unique signal values (fingerprints) from sensors or radios. After this step, in real time, observed sensor readings on the smartphone are compared to this fingerprint data to approximate indoor location. Two commonly used types of fingerprinting are discussed next.

MAGNETIC FINGERPRINTING

While the magnetometer in a smartphone is typically used to reference magnetic north, indoor environments contain many sources of noise that affect this sensor. The presence of metals, magnets, electronics, and building wiring can all affect the magnetic signature in any given location. By better characterizing these effects throughout the building, magnetometer data can be used to estimate location [8]. IndoorAtlas is a magnetic fingerprint-based localization solution provider that has teamed up with Yahoo! for building mapping in Japan [9].

RSSI FINGERPRINTING

By measuring the signal strength of received RF signals using one or more of the radios in the smartphone, a fingerprint for a given location can be established. This is by far the most popular technique for indoor localization, especially when used with Wi-Fi RF signals, which are ubiquitous in almost all indoor locales today. By characterizing an RF fingerprint throughout the localization area, an estimation of location based on this information can be established. Radio detection and ranging (RADAR) [10] is an example of a localization framework that uses Wi-Fi RSSI fingerprinting in combination with a Euclidean distance measure empirical calculation to determine indoor location. One constraint of such strategies is that the initial fingerprinting survey can be

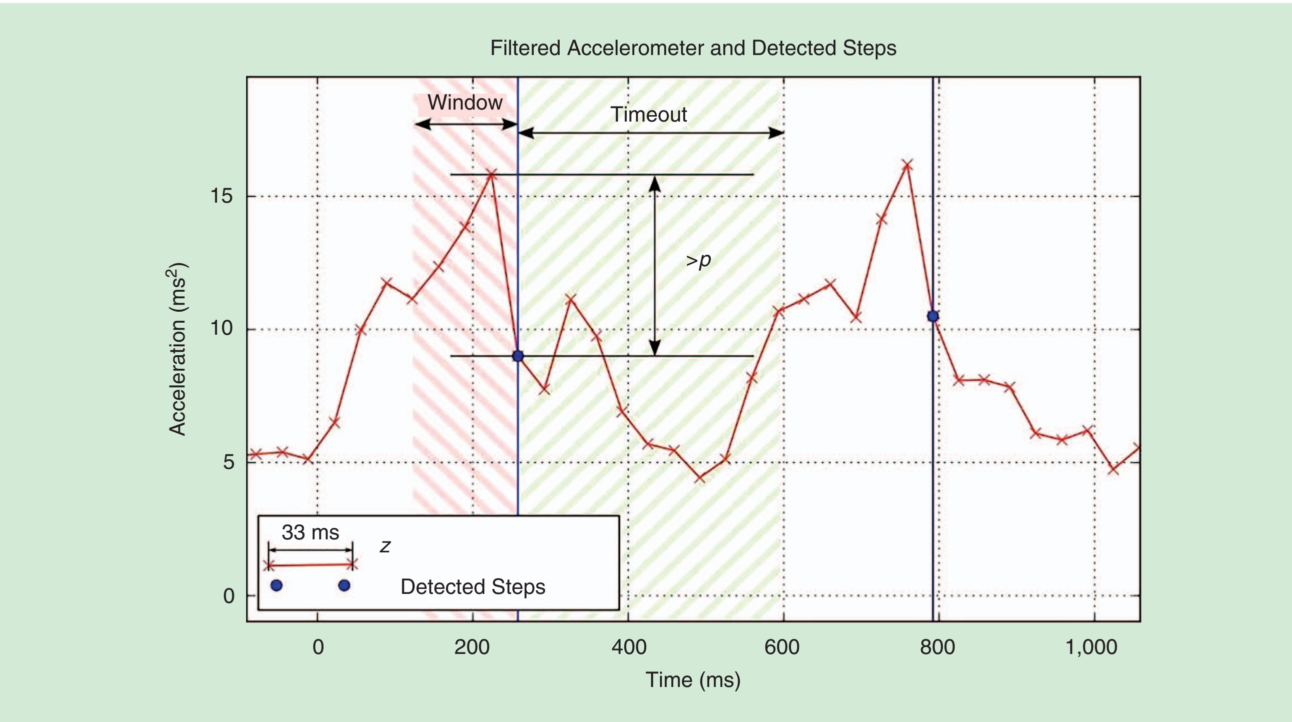

FIGURE 4. The step detection in FootPath [3].

time consuming, and the fingerprinting process may need to be repeated if RF signal sources are added, removed, or moved. Several public Wi-Fi access points (and also cellular network identification) databases are readily available [1] that can reduce survey overheads for empirical fingerprinting-based indoor localization solutions; however, the limited quantity and granularity of fingerprint data for building interiors remain a challenge. Skyhook Wireless was one of the early pioneers of Wi-Fi fingerprinting, creating an access point fingerprinting database that was originally used for localization on the iPhone [11]. Similarly, the PlaceLab indoor localization technique utilizes Wi-Fi and cellular RSSI information [12].

TRILATERATION

A series of distance estimations between the smartphone and external RF beacons can be used to estimate location. With distance measurements at a minimum of three separate known locations, a three-dimensional position relative to the beacons can be established. The various forms of distance measurement discussed next can all be used as sources of data for the purposes of trilateration.

RSSI DISTANCE ESTIMATION

The measured RSSI value changes proportionally to distance from its origin and thus can be used to estimate distance to an RF signal source. An early example of research in RSSI distance estimation using Wi-Fi radios is the EZ localization algorithm [13]. But such an estimation can be error prone because of RF interferences and multipath effects. The magnitude of a received audio signal can alternatively be used to approximate distance, although reflections, echo, and interfering objects can be sources of error for this type of estimation.

ToF OR TIME OF ARRIVAL RANGING

By measuring the time it takes for a signal to travel from a source to a receiver, the distance between the two can be estimated [14]. ToF ranging can be achieved using various types of signals such as audio, RF, or light. But the sensors in a smartphone are not configured to provide received timing with accuracies sufficient to accomplish ToF/time-of-arrival (ToA) ranging, so these strategies are typically employed using external sensors and/or beacons.

TIME DIFFERENCE OF ARRIVAL OR MULTILATERATION

Multilateration strategies involve a signal sent from a mobile point, which is received by two or more fixed points. The difference in time at which each of the fixed points receives the signal corresponds to the difference in distance between the mobile point and each of the fixed points [15]. An alternate method is to have each of the fixed points send out a signal simultaneously and to calculate the position based on the difference in time at which these signals are received by the mobile point. These strategies can be used to find the location of the mobile point in relation to the fixed points. One constraint of this approach is that the fixed points require a method for precise time synchronization. Smartphones do not contain radios that are designed for multilateration by default, so RF-based methods would require external sensors and/or beacons. Acoustic multilateration has been accomplished with smartphones using the internal speakers and/or microphones [16].

TRIANGULATION

If the angles at a minimum of two known locations for a smartphone are known, their location can be estimated. The only sensor in a typical smartphone that can estimate an angle to a known location is the magnetometer, which is prone to interference. Due to this fact, triangulation-based systems using a smartphone require the addition of other external sensors. Angle-of-arrival (AoA) techniques are often used to determine the angle between an array of receiving antennas and a transmitting source. One technique is similar to the time difference of arrival (TDoA), and is accomplished by measuring the time difference at which the signal arrives at each antenna in the array to calculate an incident angle to the array. Another method is based on spacing the antennas in the array a known wavelength apart and measuring the phase difference of the received signal between each of the antennas to calculate an incident angle [17]. An external antenna array would be required to measure AoA in smartphones as these devices do not contain such an array.

PROXIMITY ESTIMATION

The most basic form of localization utilizing RF beacons (access points) is to estimate that the position of the user is the same as the position of the beacon with the highest signal strength. This is effective for strategies where only general proximity is needed, as the positional accuracy can be low. BLE beacons and iBeacons are examples of valid point-source beacons. Aruba, a company that develops BLE-based indoor location beacons for retail stores, was acquired by Hewlett Packard Enterprise in 2015 and offers an application program interface that developers can use to deliver indoor navigation and location-relevant push notifications [18]. Ambient sounds that are present in the environment naturally or audio beacons can also be detected and used to identify the rough proximity to these sources. As smartphone microphones operate in the audible or near-audible range, the options for detecting frequencies that are not distracting to humans or animals can be limited.

VISUAL LOCALIZATION

One or more of the smartphone's cameras can be used as input data sources for localization through a variety of methods. A key requirement is that the camera must be exposed and unobstructed for these localization strategies to be effective.

VISUAL RECOGNITION

The camera on a smartphone can be used for recognition of visual cues in the environment. A company called ByteLight uses different coded pulses in overhead LED lighting within a building that can be picked up by a smartphone camera to indicate that the device is located within a certain section of that building [19].

SCENE ANALYSIS

Localization can also be accomplished through scene analysis by identifying preprogrammed landmarks and their position, observed size, and orientations relative to one another in a scene. This process is akin to the way humans visually recognize their surroundings and estimate their position relative to them.

OPTICAL FLOW

Camera information can also be important for detecting motion and rotation. A process known as *optical flow* measures the distance at which points of interest move. If the distance between the camera and the points of interest is known, the distance traveled can be extrapolated. Optical flow is commonly used for indoor flying drones by using a camera pointed at the ground to estimate change in location and speed [20]. Smartphone cameras have also been used to capture the optical flow of the room floor for direction and velocity estimation [21]. But floors that lack visual features or are reflective lead to reduced accuracy.

SUPPLEMENTARY TECHNIQUES

There are some methodologies that cannot be used for indoor localization directly but aid many of the previously discussed localization techniques to further improve localization accuracy and speed.

MAP MATCHING

These are techniques for matching sensor/signal readings to a physical floor plan. By considering geometric constraints in floor plans, location accuracy can be improved. In general, the path taken by a mobile subject should be similar to the floor plan in the map, and any deviations may be suggestive of errors. Map matching has been used in many indoor localization scenarios. For instance, FootPath [3] utilizes accelerometer and magnetic compass data for step detection and heading estimation, respectively, and then overlays this information onto a map available through OpenStreetMap, using specially designed map-matching heuristics.

PARTICLE FILTERS

Using particle filters is an extension on the concept of simple map matching. It is important to note that the motion of any mobile subject is constrained by natural laws of physics that limit the acceleration or feasibility of certain locations. This technique usually involves representing many possible estimated positions as particles on the map and then eliminating them when they defy these natural laws. The remaining particles would then represent the possible locations of the mobile subject. In [22], a framework was proposed to combine a backtracking particle filter with different levels of building-plan detail to improve indoor localization performance via dead reckoning.

There are advantages and disadvantages to each of the sensors in a smartphone.

HYBRID LOCALIZATION METHODS

There are advantages and disadvantages to each of the sensors in a smartphone as well as to each of the localization methods described thus far. For this reason, many recent efforts have focused on combining data from multiple sensors and/or utilizing multiple localization methods.

One commonly used method for combining multiple input sources is known as *linear quadratic estimation* or *Kalman filtering* [23]. The Kalman filter utilizes a previous location and multiple sensors that can estimate a change in state to arrive at a predicted current location [24]. This method has also been used for outdoor localization, combining inertial sensor data with GPS data to approximate location over time more swiftly than either of the two independently. The process for estimating the position based on multiple sensors is sometimes referred to as *sensor fusion*. Other commonly used filters for sensor fusion, particularly with inertial measurement units, are the Madgwick et al. [25] and Mahony filters [26].

The LearnLoc framework [27] combines dead reckoning, Wi-Fi fingerprinting, and machine-learning techniques to deliver a low-cost and infrastructure-free localization solution. Three supervised machine-learning techniques were considered to improve localization accuracy: k-nearest neighbor (KNN), linear regression (LR), and nonlinear regression with neural networks (NL-NN). It is important to note that only regression-based variants of these techniques were applied, as they delivered faster predictions with much lower energy requirements. LearnLoc is able to accommodate different Wi-Fi scan intervals to tradeoff energy consumption and localization error. Figure 5 summarizes the

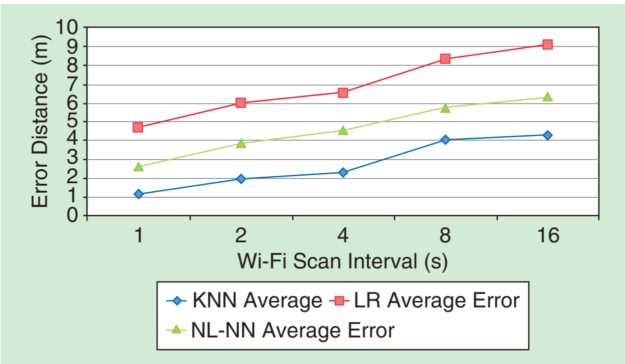

FIGURE 5. The impact of Wi-Fi scan intervals on indoor localization errors [27].

> The fact that most people carry a smartphone makes it an attractive platform for localization.

impact of Wi-Fi scan intervals on localization errors; frequent scans end up consuming more energy but also improve accuracy. All three machine-learning algorithms demonstrated a logarithmic increase in the error distance with increasing Wi-Fi scan intervals. A Wi-Fi scan interval of 4 s was chosen to balance energy consumption and localization accuracy. The three variants of LearnLoc (corresponding to the three machine-learning techniques) were compared against radar [10], FootPath (InertialNav) [3], and PlaceLab [12] for different buildings, as shown in Figure 6. It was observed that all variants of LearnLoc consistently outperformed the other techniques, and the KNN variant of LearnLoc delivered the most accurate results in all cases. LearnLoc represents one of the first studies to explore tradeoffs between energy consumption and localization accuracy on smartphones.

There also exist a few commercial offerings that utilize hybrid techniques for indoor localization. SPIRIT Navigation offers a service called *IndoorSpirit* that uses multiple data sources to localize with a smartphone, including magnetic fingerprinting, pedestrian dead reckoning, Wi-Fi fingerprinting, and map matching [28]. In 2003, Apple acquired the indoor location startup WiFiSLAM, whose core technology utilizes Wi-Fi fingerprinting, trilateration, motion sensors, TDoA, and magnetic fingerprinting in a smartphone [29]. With this data, crowdsourced trajectory mapping is done using machine learning and pattern recognition to build indoor maps over time.

Some techniques propose the combination of radio signals with unconventional noninertial sources. SurroundSense [30] establishes a fingerprint for indoor locations with a smartphone based on ambient sounds, lighting, colors, motion patterns, Wi-Fi access points, and geocentric solar magnetospheric coordinates. The currently observed fingerprint was then utilized to predict which location the user was at from a location database. Another technique called the *acoustic location processing system* (*ALPS*) [31] employs a combination of BLE transmitters and ultrasound signals to form time-synchronized beacons with a focus on minimal setup effort. ALPS uses BLE solely for time synchronization, whereas ultrasound chirps are used for ranging through TDoA. This process allows for the automated computation of beacon locations, saving the manual effort. In [32], the IDyLL indoor localization system uses the combination of dead reckoning with photosensors on smartphones. Typical luminary sources (including incandescent, fluorescent, and LED) are often uniquely (sometimes evenly) spaced in many indoor environments. IDyLL uses an illumination peak-detection algorithm and fuses this information with dead reckoning and map matching to achieve fine-grain localization.

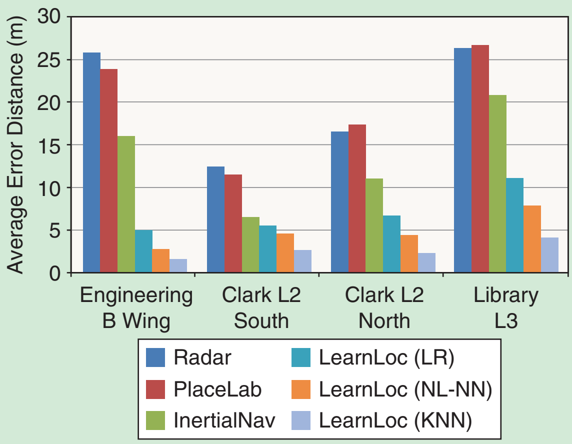

FIGURE 6. A comparison of indoor localization techniques with different building types [27].

CHALLENGES

Despite the exciting developments in the area of indoor localization in recent years, a number of challenges still remain. Different use cases require disparate levels of accuracy and have varying requirements for deployed infrastructure and cost; thus, a single localization solution may not be suitable for all scenarios.

EVALUATION

Location accuracy is often a focus of research and comparison of techniques. One area for improvement is the standardization of measurement techniques, environments, and use cases that would lend itself to a better comparative benchmarking of proposed approaches. These types of analysis tools, metrics, and benchmarks could help to minimize ambiguity in comparison and speed the pace of research by quickly highlighting some of the more promising solutions for a particular use case.

INFRASTRUCTURE AND COST

The use of additional sensors and beacons can greatly increase indoor localization accuracy but also increase deployment cost. Many research efforts are thus focused on smartphone localization without the need for infrastructure or additional sensors, as this is the lowest barrier-to-entry solution. Other solutions focus on minimizing or hiding beacon infrastructures [33]. More effort is needed to aggressively reduce costs for localization. For example, techniques that can calculate the optimal placement of beacons in an indoor environment (based on wireless signal type, overlap, coverage, and so on) can lead to the minimization of beacons required for accurate localization, which can help reduce costs associated with localization.

SETUP REQUIREMENTS

Fingerprinting, mapping, calibration, and characterization can aid in localization but usually come at the cost of added complexity and time required. Changes to the environment can sometimes necessitate these efforts to be repeated. A fingerprint or map-based system may suffer from reduced accuracy or inability to localize in environments where this information is not already available. Some research has been done in the areas of crowdsourced mapping and fingerprinting, on-the-fly fingerprinting, and iterative map learning.

SENSOR ERROR

RF signals are subject to noise, multipath interference, and variable propagation performance in indoor environments. Some locations are more problematic than others, and very few research efforts account for these sources of interference. Magnetometer-based localization methods often suffer from interference in the presence of metals as well as magnetics and electronics. Inertial sensor-based solutions have challenges associated with drift, irregular movement patterns, and accumulation of error. Research in the area of filtering and calibration for dead reckoning is essential to reduce these sources of error [34].

POWER

The frequent use of radios and/or sensors in a smartphone for localization can come at the price of high power overhead. Efforts to balance location accuracy with battery life are ongoing [35]. Different scenarios or usage patterns may require different localization strategies, and solutions are needed that can employ a customized approach based on the situation.

PERFORMANCE REQUIREMENTS

Some localization strategies employ machine learning, image processing, or complex signal processing. Some of these types of operations can require high-processing or memory overhead, which may restrict the methods that can be viably deployed on a smartphone. In general, more resource-intensive strategies reduce battery life and user quality-of-service.

NEW SENSORS AND RADIOS

Smartphones are currently packed with sensors and radios, but there is a continuous push to increase the capabilities of these devices. Additional sensors or radios that specifically target indoor localization have been proposed for smartphones. The determination of which new sensors/radios would be the best choice and the design of solutions involving them are open questions.

CONCLUSIONS AND FUTURE DIRECTIONS

The variety of sensors and radios available in today's smartphones, and the fact that most people carry a smartphone, make it an attractive platform for localization. The evolution of the smartphone will continue to alter the landscape of how we approach localization. Any integration of new sensors specifically for localization into smartphone devices may drastically shift our approach to this problem. Creative application of machine learning or sensor fusion algorithms can also help to integrate the strengths of various smartphone sensors/radios and maximize the potential of currently available smartphone technology. As smartphone technology improves, the ability to run more complex algorithms for localization also increases. The holistic goal of creating a single indoor localization strategy using commodity smartphones with no additional infrastructure, calibration, or setup that is highly accurate and low power across all use cases is a work in progress. It may be that this panacea for indoor localization is simply not feasible and that a portfolio of solutions is the optimal approach.

Inevitably, indoor localization is poised to fill a gap left by GNSSs in environments without coverage. Applications that currently rely on a GNSS in outdoor environments would be well served to have an alternative solution available as necessary, and this is something that can benefit from research on indoor localization. The many potential industry and consumer uses for this technology as well as government mandates for improved indoor localization ensure that there will continue to be a focus on this theme from both academia and industry for a long time.

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REFERENCES

[1] (2017, Apr. 11). PerfLoc: Performance evaluation of smartphone indoor localization apps. [Online]. Available: https://perfloc.nist.gov/perfloc.php/

[2] M. Romanovas, V. Goridko, A. Al-Jawad, M. Schwaab, M. Traechtler, L. Klingbeil, and Y. Manoli, "A study on indoor pedestrian localization algorithms with foot-mounted sensors," in *Proc. Int. Conf.*

Indoor Positioning and Indoor Navigation (IPIN), Sydney, Australia, 2012, pp. 1–10.
[3] J. Link, P. Smith, N. Viol, and K. Wehrle, "FootPath: Accurate map-based indoor navigation using smartphones," in *Proc. Int. Conf. Indoor Positioning and Indoor Navigation (IPIN)*, Guimaraes, Portugal, 2011, pp. 1–8.
[4] J. T. Levi and W. Robert, "Dead reckoning navigational system using accelerometer to measure foot impacts," U.S. Patent 5583776, Dec. 10, 1996.
[5] J. W. Kim, H. J. Jang, D.-H. Hwang, and C. Park, "A step, stride and heading determination for the Pedestrian Navigation System," *J. Global Positioning Syst.*, vol. 3, no. 1–2, pp. 273–279, 2004.
[6] R. Harle, "A survey of indoor inertial positioning systems for pedestrians," *Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1281–1293, 2013.
[7] U. Steinhoff and B. Schiele, "Dead reckoning from the pocket—An experimental study," in *Proc. IEEE Int. Conf. Pervasive Computing and Communications (PerCom)*, Mannheim, Germany, 2010, pp. 162–170.
[8] Q. Wang, H. Luo, F. Zhao, and W. Shao, "An indoor self-localization algorithm using the calibration of the online magnetic fingerprints and indoor landmarks," in *Proc. Int. Conf. Indoor Positioning and Indoor Navigation (IPIN)*, Alcala de Henares, Spain, 2016, pp. 1–8.
[9] B. Frederick. (2016, Feb. 25). IndoorAtlas, Yahoo team geomagnetic building mapping in Japan. *Mobile Marketing Daily*. [Online]. Available: https://www.mediapost.com/publications/article/269899/indooratlas-yahoo-team-geomagnetic-building-mappi.html
[10] P. Bahl, and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. 19th Annu. Joint Conf. IEEE Computer and Communications Societies (IEEE INFOCOM)*, Tel. Aviv, Israel, 2000, pp. 775–784.
[11] J. Wortham. (2009, May 31). Cellphone locator system needs no satellite, *New York Times*. [Online]. Available: http://www.nytimes.com-/2009-/06/01/technology/start-ups/01locate.html
[12] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter, J. Tabert, P. Powledge, G. Borriello, and B. Schilit, "Place lab: Device positioning using radio beacons in the wild," in *Proc. Int. Conf. Pervasive Computing (PerCom)*, 2005, pp. 116–133.
[13] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proc. 16th Annu. Int. Conf. Association for Computing Machinery Mobile Computing and Networking (ACM MobiCom'10)*, Chicago, IL, 2010, pp. 173–184.
[14] T. Karalar and J. Rabaey, "An RF ToF based ranging implementation for sensor networks," in *Proc. IEEE Int. Conf. Communications 2006*, pp. 3347–3352.
[15] F. Gustafsson and F. Gunnarsson, "Positioning using time-difference of arrival measurements," in *Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing 2003 (ICASSP'03)*, Hong Kong, China, pp. VI-553–556.
[16] F. Höflinger, R. Zhang, J. Hoppe, A. Bannoura, L. M. Reindl, J. Wendeberg, M. Bührer, and C. Schindelhauer, "Acoustic self-calibrating system for indoor smartphone tracking," in *Proc. Int. Conf. Indoor Positioning and Indoor Navigation (IPIN)*, Sydney, Australia, 2012, pp. 1–9.
[17] J. Xiong and K. Jamieson, "ArrayTrack: A fine-grain indoor location system," in *Proc. 10th USENIX Symp. Networked Systems Design and Implementation (NSDI)*, Lombard, IL, 2013, pp. 71–84.
[18] B. Krulwich. (2015, Dec. 2). Hewlett Packard Enterprise: Aruba driving blue dot indoor location into the big leagues. *Seeking Alpha*. [Online]. Available: https://seekingalpha.com/article/3727956-hewlett-packard-enterprise-aruba-driving-blue-dot-indoor-location-big-leagues
[19] S. Cangeloso. (2013, Mar. 25). Forget WiFiSlam—ByteLight uses LEDs for indoor positioning. *ExtremeTech*. [Online]. Available: https://www.extremetech.com/extreme/151068-forget-wifislam-bytelight-uses-leds-for-indoor-positioning
[20] N. Gageik, M. Strohmeier, and S. Montenegro, "An autonomous UAV with an optical flow sensor for positioning and navigation," *Int. J. Adv. Robotic Syst.*, vol. 10, no. 10, pp. 1–9, 2013.
[21] J. Á. Bitsch, F. Gerdsmeier, P. Smith, and K. Wehrle, "Indoor navigation on wheels (and on foot) using smartphones," in *Proc. Indoor Positioning and Indoor Navigation (IPIN)*, Sydney, Australia, 2012, pp. 1–10.
[22] S. Beauregard, Widyawan, and M. Klepal, "Indoor PDR performance enhancement using minimal map information and particle filters," in *Proc. IEEE/Institute of Navigation Position, Location and Navigation Symp.*, Monterey, CA, 2008, pp. 141–147.
[23] R. E. Kalman, "A new approach to linear filtering and prediction problems," *J. Basic Eng.*, vol. 82, no. 1, pp. 34–45, Mar. 1960.
[24] H. Hellmers, A. Norrdine, J. Blankenbach, and A. Eichhorn, "An IMU/magnetometer-based Indoor positioning system using Kalman filtering," in *Proc. Indoor Positioning and Indoor Navigation (IPIN)*, Montbeliard-Belfort, France, 2013, pp. 1–9.
[25] S.O.H. Madgwick, A.J.L. Harrison, and R. Vaidyanathan, "Estimation of IMU and MARG orientation using a gradient descent algorithm," in *Proc. IEEE Int. Conf. Rehabilitation Robotics (ICORR)*, Zurich, Switzerland, 2011, pp. 1–7.
[26] R. Mahony, T. Hamel, and J. M. Pflimlin, "Complementary filter design on the special orthogonal group," in *Proc. 44th IEEE Conf. Decision and Control (CDC)*, Seville, Spain, 2005, pp. 1477–1484.
[27] S. Pasricha, V. Ugave, C. W. Anderson, and Q. Han, "LearnLoc: A framework for smart indoor localization with embedded mobile devices," in *Proc. Int. Conf. Hardware/Software Codesign and System Synthesis (CODES+ISSS)*, Amsterdam, The Netherlands, 2015, pp. 37–44.
[28] L. Privat. (2015, Apr. 22). SPIRIT Navigation wins 2nd prize in Microsoft indoor location competition. *GPS Business News*. [Online]. Available: http://www.gpsbusinessnews.com/SPIRIT-Navigation-Wins-2dn-Prize-in-Microsoft-Indoor-Loc-Competition_a5425.html
[29] M. Panzarino. (2013, Mar. 25). What exactly WiFiSLAM is, and why Apple acquired it. *The Next Web*. [Online]. Available: https://thenextweb.com/apple/2013/03/26/what-exactly-wifislam-is-and-why-apple-acquired-it
[30] A. Martin, C. Ionut, and C. Romit, "SurroundSense: Mobile phone localization via ambience fingerprinting," in *Proc. Association for Computing Machinery 15th Annu. Int. Conf. Mobile Computing and Networking (MobiCom)*, Beijing, China, 2009, pp. 261–272.
[31] P. Lazik, N. Rajagopal, O. Shih, B. Sinopoli, and A. Rowe, "ALPS: A Bluetooth and ultrasound platform for mapping and localization," in *Proc. SenSys 13th Association for Computing Machinery Conf. Embedded Networked Sensor Systems*, Seoul, South Korea, 2015, pp. 73–84.
[32] Q. Xu, R. Zheng, and S. Hranilovic. "IDyLL: Indoor localization using inertial and light sensors on smartphones," in *Proc. Association for Computing Machinery Int. Joint Conf. Pervasive and Ubiquitous Computing*, 2015, pp. 307–318.
[33] H. Nyqvist, M. Skoglund, G. Hendeby, and F. Gustafsson, "Pose estimation using monocular vision and inertial sensors aided with ultra wide band," in *Proc. Int. Conf. Indoor Positioning and Indoor Navigation (IPIN)*, 2015, pp. 1–10.
[34] F. Alaoui, D. Betaille, and V. Renaudin, "A multi-hypothesis particle filtering approach for pedestrian dead reckoning," in *Proc. Int. Conf. Indoor Positioning and Indoor Navigation (IPIN)*, 2106, pp. 1–8.
[35] Y. Wang, Y. Bu, Q. Jin, and A. Vasilakos, "Energy-efficient localization and tracking on smartphones: Design principle and solutions," in *Proc. 11th Int. Conf. Future Technologies (CFI)*, 2016, pp. 29–35.
[36] A. Berenguer, J. Goncalves, S. Hosio, D. Ferreira, T. Anagnostopoulos, and V. Kostakos, "Are smartphones ubiquitous? An in-depth survey of smartphone adoption by seniors," *IEEE Consum. Electron. Mag.*, vol. 6, no. 1, pp. 104–110, Jan. 2017.
[37] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The Internet of things is the backbone," *IEEE Consum. Electron. Mag.*, vol. 5, no. 3, pp. 60–70, July 2016.