IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 4, 2022, accepted April 27, 2022, date of publication May 2, 2022, date of current version May 12, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3171859

Constrained Localization: A Survey

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ABSTRACT Indoor localization techniques have been extensively studied in the last decade. The well-established technologies enable the development of Real-Time Location Systems (RTLS). A good body of publications emerged, with several survey papers that provide a deep analysis of the research advances. Existing survey papers focus on either a specific technique and technology or on a general overview of indoor localization research. However, there is a need for a use case-driven survey on both recent academic research and commercial trends, as well as a hands-on evaluation of commercial solutions. This work aims at helping researchers select the appropriate technology and technique suitable for developing low-cost, low-power localization system, capable of providing centimeter level accuracy. The article is both a survey on recent academic research and a hands-on evaluation of commercial solutions. We introduce a specific use case as a guiding application throughout this article: localizing low-cost low-power miniature wireless swarm robots. We define a taxonomy and classify academic research according to five criteria: Line of Sight (LoS) requirement, accuracy, update rate, battery life, cost. We discuss localization fundamentals, the different technologies and techniques, as well as recent commercial developments and trends. Besides the traditional taxonomy and survey, this article also presents a hands-on evaluation of popular commercial localization solutions based on Bluetooth Angle of Arrival (AoA) and Ultra-Wideband (UWB). We conclude this article by discussing the five most important open research challenges: lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, and standardization.

INDEX TERMS Constrained localization, tracking, exploration and mapping, real-time location systems, Internet of Things, wireless sensor networks, DotBot, low-cost robots, low-power operation, Bluetooth AoA, UWB.

I. INTRODUCTION

Localization is a technique for estimating the position of an object or a person in a certain environment. While Global Positioning System (GPS) is widely used for the outdoor localization, with meter-level positioning accuracy in the best cases, it doesn't work indoors. Also, numerous applications require a much better, sub-meter or sub-decimeter level localization accuracy. Being a very popular research topic in recent years, indoor localization is becoming a well-studied research field, with research publications and commercial products emerging to improve indoor localization. Studies have been conducted in many areas, from the core technologies used in localization systems to positioning algorithms and signal processing [1]. Obtaining the location of a device or a user is essential to many applications, including in health care, industrial production, autonomous vehicles, smart cities, and smart buildings [2], [3].

Health care applications such as clinical motion analysis, physiotherapy and rehabilitation could strongly benefit from localization solutions. By installing sensors on a patient's body for tracking body movements and micro movements, health professionals could significantly improve medical diagnosis and treatment [4], [5]. In case of spreading of infectious disease inside the health care facility, contact tracing is essential in order to interrupt ongoing transmission and reduce the spread of an infection [6], [7]. Localization is extremely important in industrial facilities. In a manufacturing plant, we want to know the position of persons, tools and materials inside a production line, which allows the development of indoor localization-based safety system [8]. Industrial facilities such as warehouses and other cluttered

The associate editor coordinating the review of this manuscript and approving it for publication was Cong Pu.

environments use robotic arms with sophisticated localization capabilities to perform retrieval tasks [9]. Another example application where localization is required are autonomous vehicles. Using a localization system, autonomous car or a mobile robot is capable to estimate its pose in a map based on on-board sensors information [10]. In smart cities and smart buildings, knowing the location of a user and/or device paves the way for many new applications like public safety, tracking services and robot guidance (in-building) [11].

Different applications place different requirements on the localization systems. There are many localization techniques available, all having different constraints in terms of line-of-sight deployment, update rate, accuracy, battery lifetime and security [12]. It is important to be able to navigate the trade-offs to find the best match between the application and localization system.

As a specific application that needs indoor localization, we introduce the DotBot, a small form-factor low-cost robot for educational and research purposes. The latest version of the DotBot is depicted in Fig. 1. Hundreds of these miniature IoT robots with networking capabilities are deployed as a swarm, and are used to develop swarm navigation algorithms, for example for exploration and mapping [13]. Precise continuous localization of these robots is essential in order to give the swarm spatial context, and allow the mapping of a certain environment. This use case results in several constraints when trying to estimate the robot's position. First, the cost of the localization system needs to be very low, as the total cost of a DotBot must be below USD 20. Second, sub-decimeter localization accuracy is needed to allow the precise mapping. Third, the refresh rate of the DotBot's location has to be fast enough to match the movement speed of the robots, at least 10 Hz. Fourth, the scalability of this localization system is crucial, as there can be hundreds or thousands of DotBots in a swarm. Fifth, the low-power operation of the mobile device needs to ensure the continuous localization of DotBots for years. Finally, these robots need to be small in size to allow the mapping of the environment that is not accessible by people, have the ability to be easily integrated in an existing system and include a small wireless sensor for monitoring certain parameters.

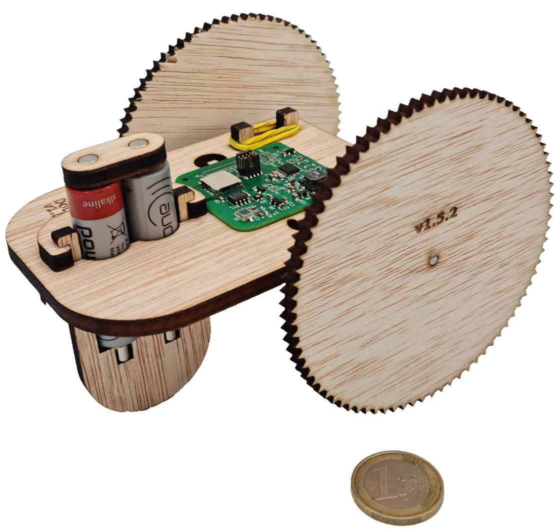


FIGURE 1. **DotBot: a low-cost, micro-robot for educational and research purposes in networking and swarm robotics.**

In order to design a localization system that overcomes the constraints that we identify in our DotBot use case, we need a thorough analysis of the state-of-the-art in the field of indoor localization, in both academic research and commercial trends. We therefore identify the latest technologies and techniques suitable for being used in low-cost and low-power systems, capable of providing precise localization. Specifically, we survey both recent academic work on indoor localization, and give hands-on evaluations of the most important off-the-shelf commercial solutions used in localization today. By surveying recent academic work and evaluating the most important commercial products today, this article helps researchers and advanced R&D engineers choose suitable technology and techniques when designing a constrained localization system.

This article is tailored to the researcher and advanced engineer who, either is new to the field of indoor localization, or wants a refresher to stay up-to-date with the technology. Moreover, it provides the reader with a comprehensive deep-dive into the state of the art of both academic studies and commercial solutions, a matter-of-fact hands-on direct evaluation of the most important indoor localization solutions available today, and a clear understanding of the open challenges and trends to expect in the next 3-5 years.

A. RELATED WORK

Indoor localization is a growing research field, with several commercial solutions on the market. A good body of publications related to indoor localization has emerged in the recent years. Several survey articles provide a deep analysis of the research advances in this field.

Some survey papers focus on a specific technique. Alarifi *et al.* [14] present a thorough analysis of UWB-based localization systems. The authors discuss UWB positioning systems from the perspective of different techniques used in the development. Yang *et al.* [15] present a survey of academic work done on using the inertial sensors in smartphones in order to assist/enable localization. The authors put a particular focus on combining inertial sensors with WiFi fingerprinting. Gu *et al.* [16] give a review of the work conducted in improving the indoor localization with a spatial context. The authors focus on spatial context in the form of maps, grid models, graph models and landmarks.

There are a number of survey papers which provide a more general overview of indoor localization, comparable in scope to this article. Xiao *et al.* [17] present a survey on indoor localization from the device perspective. Authors review the research done on device-based and device-free indoor localization. Device-based localization requires a user or a target to carry the locating device, whereas the device-free localization monitors the changes in the wireless signal without any device attached to the tracking object. Laoudias *et al.* [18] provide a detailed overview of the enabling technologies for localization, tracking and navigation in wireless networks. The authors discuss solutions and algorithms in areas such as: cellular network localization, WLAN-based localization, range-free localization, data fusion, vertical positioning, mobility state estimation and indoor mapping. Zafari *et al.* [19] provide a deep analysis of different indoor localization techniques and technologies. The authors present different research papers on indoor localization, dividing them into two main categories: monitor based localization (MBL) and device based localization (DBL).

B. CONTRIBUTIONS

The following are key contributions of this article.

1) Up-to-date survey of both academic papers on indoor localization that were published from 2015 to 2022. We propose a taxonomy and classify the papers in order to highlight their pros and cons.
2) A comprehensive survey of commercial trends and technologies. This aspect is mostly absent from other survey papers, yet tremendously important. Companies developing localization solutions make a real contribution to the field, even if not in the form of academic papers, and it is important for a survey paper to include their innovations. And since these solutions are commercially available, they are typically widely used, so it is important to expose the readership to them.
3) Hands-on evaluation of the most important commercial solutions on the market today. Presented experiments highlight the performance and constraints of the Bluetooth AoA estimation and UWB ranging. Bluetooth AoA estimation experiments were performed using Texas Instruments and Nordic Semiconductor evaluation kits. UWB ranging measurements were acquired using Decawave DWM1001-DEV evaluation boards.
4) DotBot localization use case as a guiding application throughout this article. This use case is interesting as it combines the requirements of cm-level accuracy, low-power operation and > 10 Hz refresh rate. Although we survey a wide range of localization techniques, using this use case gives the article a precise focus as we structure the narrative of the paper as a quest for a localization technique which satisfies our use case.
5) A detailed discussion about the fundamentals in indoor localization, lessons learned from this study and the main research challenges we identify. These challenges will serve as motivation for future work in the field of indoor localization.

C. REMAINDER OF THE ARTICLE

The remainder of this article is organized as follows.

- Section II introduces the fundamentals in localization. In this section we present different localization techniques, the latest commercial trends in localization technologies and two main architecture types.
- Section III shows different classification criteria that we choose for classifying the recent research on indoor localization. We introduce five criteria: *Line of Sight (LoS) requirement, accuracy, update rate, battery life and cost*.
- In Section IV we present the recent academic research on indoor localization. Here we introduce the papers based on different technologies organized in three groups: light-based, sound-based and RF-based.
- In Section V we present a hands-on evaluation of some RF-based commercial products. We present the AoA estimation experiments using Texas Instruments and Nordic Semiconductor Bluetooth Direction Finding evaluation kits. We also present ranging estimation experiments of commercial UWB evaluation boards from Decawave.
- In Section VI we discuss the lessons learned from the survey of academic research papers and hands-on evaluation of RF-based commercial products.
- Section VII highlights some of the main open research challenges in indoor localization.
- In Section VIII we give the conclusion of this article.

II. FUNDAMENTALS

In any localization system there are three fundamental aspects: localization technique, localization technology, architecture type.

The localization *technique* is the way of estimating the position of the mobile device. There are many different localization techniques which can be combined with different technologies in order to develop a localization system. However, a specific localization technique usually gives the best results when combined with a particular localization technology. Thus, we need to carefully match these two fundamental elements of the localization system in order to meet the application requirements and have satisfying results.

The localization *technology* represents the physical "core" method used in the localization system. In this article, we classify localization technologies into three main groups: light-based, sound-based, RF-based.

When designing a localization system, many considerations have to be made according to the application requirements [20]. Certainly, one of the first aspects that need to be examined is the *architecture*. Architecture constraints determine the top-level characteristics of the localization system. It defines what element knows the position of the mobile devices: the system or the mobile device. This consideration has a big impact on scalability and security. Having the mobile device determine its own position without relying on the localization infrastructure scales perfectly, as there is no additional cost to the localization infrastructure when going from 10 mobile devices to 1,000. This is the approach taken in GPS. The alternative is for the localization system to have a centralized positioning engine which communicates with the mobile devices and is responsible for computing their location. This architecture approach is usually implemented in specific environments and applications, such as localizing assets in warehouses or tracking people in the hazardous environments.

In this section we introduce the most popular localization techniques. We survey the most promising technologies and commercial trends used for localization that fits the requirements of the DotBot localization use case. Lastly, we present the two main architecture types in localization systems.

A. LOCALIZATION TECHNIQUES

This section focuses on the most widely used techniques for low-power and low-cost localization systems. We introduce the following techniques: Receive Signal Strength (RSS) and fingerprinting, Time of Flight (ToF), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA). Other techniques such Phase of Arrival (PoA) and Channel State Information (CSI) are not in the scope of this paper. For detailed information about PoA and CSI localization techniques, the interested reader is referred to [17], [21], [22].

RSS-based localization is the most commonly used technique for the indoor localization. This is mainly due to market availability of low-cost and low-power SoCs that generate RSS readings through the RSSI. The RSSI represents the value of the signal's power at the receiver side. The distance between the two devices or the radius of a sphere is calculated as the function of RSSI, where a larger RSSI value means a smaller distance between transmitter and receiver. The distance d between the two devices can be derived from the following equation [23]:

$$RSSI = -10n \log_{10}(d) + C \tag{1}$$

where, n is the path loss exponent factor and C is the fixed constant. Having one mobile device and at least three anchor devices it is possible to obtain the 2D position of the tag using trilateration.

The biggest constraint of this technique is the poor localization accuracy due to the nature of the radio signals. Multi-path and fading effects can severely affect the distance estimations, as the signal power at the receiver changes dramatically with slight changes of the mobile device's position and/or the environment conditions. When developing RSS-based localization solution using simulations the researcher must employ a suitable signal propagation model [24]. Some researchers use popular signal propagation models like Free Space Model (FSM) and Log Normal Shadow Fading (LNSM), while some design their own path loss models, for specific use case [25]. In the case of real-world deployments, the environment changes over time. People move across the building, furniture gets rearranged, WiFi traffic changes. This results in dynamics of wireless channels on all frequencies. When evaluating RSS-based solution, we need to choose a testbed with dynamics in order to have good validity of our solution [26]. However, localization systems based on the RSSI readings leverage its low-cost and low-power properties and they are a good choice for many applications. This technique is especially useful if the application requirements are proximity detection or the room-level localization accuracy. In order to improve the accuracy of the RSSI-based systems researchers employ fingerprinting. This method comprises two steps, offline and online phase. In the offline phase the RSSI readings at known locations are collected and stored. These readings are compared with the RSSI in the online phase to better estimate the mobile device's position. This method usually employs some machine learning method such as k-Nearest Neighbor (kNN), Neural Networks (NN), or Support Vector Machine (SVM). Although, the fingerprinting method improves the accuracy of RSSI-based localization systems, it requires the knowledge of the environment and needs more computational power.

ToF is a technique where the distance between two devices is calculated as a function of the signal propagation speed and the time between the signal's transmission and reception. ToF is the difference between Time of Transmission (ToT) and Time of Arrival (ToA). When the ToF is calculated for the RF signal propagation, the distance between the two devices is obtained by multiplying ToF measurements with the speed of light. In the case of sound-based localization systems, the ToF is multiplied with the speed of sound in the given medium. Fig. 2 illustrates the basic ToF calculation in the Two Way Ranging (TWR) method. Here, the initiator device sends a poll message for ranging to the responder and records its transmit time (TX). The responder records its reception (RX) and TX times, and sends the message back to the initiator. The distance between the two devices is calculated per (2).

$$d = \frac{(t4 - t1) - (t3 - t2)}{2} v \tag{2}$$

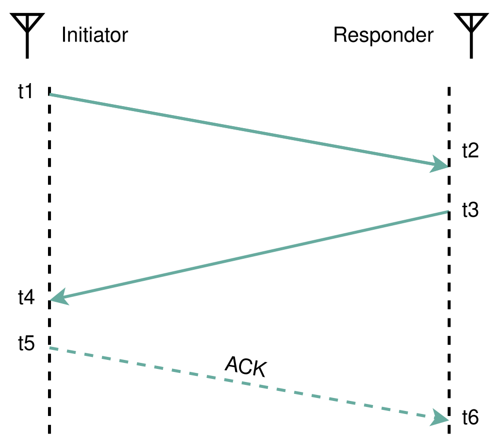


FIGURE 2. Time of Flight technique.

In (2), d is the distance between initiator and responder, v is the propagating speed of the signal, $t1$, $t2$, $t3$ and $t4$ are TX and RX timestamps shown in Fig. 2. The precision of the ToF calculation depends on many factors such as radio environment, sampling rate and drift of the local crystal oscillators. The latter is especially problematic when devices need to be time synchronized. In order to avoid the use of the precise time synchronization there are different ways of calculating ToF like Double-Sided TWR (DS-TWR) [27], where we can minimize the ToF estimation error induced by the crystal oscillators.

TDoA uses the relative difference in the signal's arrival time at the receiver side to calculate the device's location. TDoA is the core technique used in GPS for outdoor positioning and navigation. At least four anchor devices with known positions are needed to calculate the 3D location of the tag device. Unlike the TWR method, TDoA doesn't require full duplex communication between the tag and the anchors. What is needed is precise sub-nanosecond time synchronization between anchor devices [28].

AoA is a technique of estimating the angle at which the signal arrives at the receiver. In order to allow the calculations of the AoA, the receiver needs to be equipped with an antenna array, where the distance between adjacent antennas is less than half of the signal's wavelength [29]. To obtain a 3D location of the tag, at least three antenna arrays at different locations are necessary, if the antenna array consists of antennas positioned in a line, per Section V-A. Triangulation is then performed to obtain the location of the mobile device [30]. Fig. 3 illustrates how to calculate the AoA of the signal received by an antenna array. The signal's AoA φ is calculated per (3).

$$\varphi = \arcsin \frac{\alpha\lambda}{2\pi d} \tag{3}$$

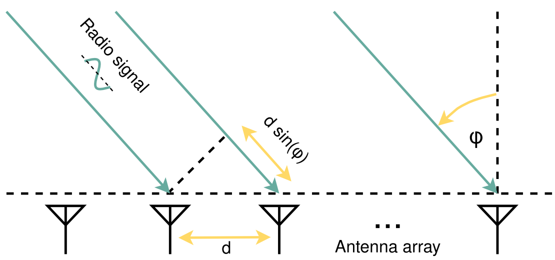


FIGURE 3. AoA estimation using antenna array.

In (3), λ is the wavelength of the incoming signal, α is the phase difference, and d is the distance between the two antennas. These types of the AoA estimations are constrained with complex RF design of the antenna arrays, multi-path propagation and larger localization error if the tag is positioned further away from the receiver. Another type of AoA estimation is used in lighthouse localization. In this technique, AoA is estimated by calculating the time between the synchronization laser pulse and horizontal and vertical laser sweep of the lighthouse. By knowing the angular speed of the laser sweep and the time difference between the pulses at the receiver, it is possible to calculate the angle of the receiver in reference to the lighthouse. For detailed explanation regarding this technique the readers are referred to [31].

A *Hybrid* localization approach combines the aforementioned techniques to improve the localization system. Typically, ToF and AoA are combined to improve the accuracy of the localization system. Combining these two techniques, a smaller number of anchor devices is needed to locate a tag in a 3D space. Even if the focus is not on having smaller number of infrastructure anchor devices, fusing the measurements from the different localization techniques through the carefully selected filter (e.g. Extended Kalman Filter) could largely improve the localization accuracy.

B. LOCALIZATION TECHNOLOGIES

Different localization technologies offer different capabilities and performance in terms of accuracy, range, battery-life, availability and cost [32]. Depending on the application type and user requirements, the designer needs to choose the localization technology best suited for their needs. In this paper, we divide the different localization technologies into three main groups, depending on the fundamental physical phenomena used. We introduce these technologies as light-based, sound-based and Radio Frequency (RF) based. Virtually all practical localization solutions use one of these physical phenomena at its core. There are numerous constraints when using these technologies in indoor localization. Considering our use case of localization of the miniature DotBot robots (Section I), we focus on low-power and low-cost technologies which are available on the market.

Light-based technologies use the optical and infrared part of the Electromagnetic (EM) spectrum. When used in the low-power indoor positioning systems, they are constrained with the reduced range of a couple of meters as well as with the LoS requirement, because light cannot penetrate obstacles. However, they usually offer millimeter-level localization accuracy, which makes them suitable for robot tracking and navigation applications, as well as a high-speed data transfer, given their large signal bandwidth. Some of the most popular light-based localization technologies used in recent research are: Visible Light Positioning (VLP), Infrared (IR), and image-based localization.

- *VLP* typically use photodiodes as a light source [33]. Multiple transmitters send beacons as light signals to the receiver. The receiver's position is then estimated with respect to the transmitter's locations, using RSS, ToF, TDoA, or AoA.
- *IR* technology is used in localization and tracking of resource-constrained mobile robots because of its millimeter-level accuracy and low-cost. As one of the representatives of this technology, lighthouse localization uses IR lasers which sweep space in two different planes. The receiver device decodes the received IR pulse which contains the information about the current angle with respect to the lighthouse transmitter. IR lighthouse localization is used in Virtual Reality (VR) systems such as HTC VIVE [34]. The core concept of the lighthouse localization was proposed by Römer *et al.* [35] in 2003 as a localization system for "Smart Dust", cubic millimeter scale sensor nodes.

- *Image*-based systems like Motion Capture use cameras to track the movements of objects with great precision, with some commercial systems reporting the positional error less than 0.3 mm and rotational error less than 0.05 ° [36]. These systems are usually used in the entertainment industry, sports science, medical applications, animations [37]–[39]. The main disadvantage of these systems is their high price. In case of OptiTrack motion capture system a single motion capture camera can cost up to 6000 USD, and in order to cover $5 \times 5 \times 2$ m the system needs at least 8 cameras for animation applications [36]. Consumer camera-based localization systems include Azure Kinect [40], which offers a Computer Vision capabilities. This device allows for the development of the motion tracking applications at lower costs [41], [42].

Sound-based localization systems use the speed of sound in the air and ToF technique to compute the distance between two devices. To locate a device, three or more anchor devices are required and a multilateration algorithm is used. Because the speed of sound is orders of magnitude lower than the speed of light, using sound allows the system to be less time sensitive and typically offers centimeter-level precision [43]. Similar to light-based technologies, sound cannot penetrate objects and walls. In a low-power setting, its range is limited to a few meters. In sound-based localization systems, the two common approaches are acoustic-based and ultrasound-based localization.

- *Acoustic*-based localization systems have the big advantage in the availability of microphone devices in smartphones. The ubiquitous microphones offer a great commercial opportunity, similar to WiFi- and Bluetooth-based localization systems. Acoustic-based localization systems use the audible band of < 20 KHz and low-power audio signals, which should not be hearable. However, the big challenge presents the signal reconstruction at the microphone, due to the sampling rate limitations and the signal's low power. Also, a big concern for the users could be the security and privacy issues, which need to be carefully examined.
- *Ultrasound* is the most common sound-based localization technology. Ultrasound uses frequencies above the hearing threshold of humans, which allows for a bigger transmit power to make them easier to detect on the receiver's side. Ultrasound-based localization solutions require synchronization, and thus these devices usually contain additional RF-based or light-based communication capabilities for time synchronization. There are some commercial systems on the market based on the ultrasound that allows the precise tracking of assets and people. One of these systems is offered by Marvelmind [44] which allows centimeter level precision. Their devices include ultrasound transceivers and 915/868 MHz or 433 MHz radios for synchronization and communication. Both stationary and mobile devices are battery-powered but need frequent battery recharge, depending on the update rate. The longest operation time without recharging is around 1 month at 1 Hz update rate for a stationary device, and 12 h at 8 Hz update rate for a mobile device.

RF-based localization solutions are the most common and there is a big research interest in the last decade in this field. Different RF-based technologies are used in combination with different localization techniques in order to provide the necessary accuracy according to the application demands [45]–[47]. Despite the fact that light-based and sound-based technologies provide centimeter or even millimeter level precision, their biggest constraint is the LoS requirement and reduced range. RF-based technology can leverage the NLoS as well as the larger range in order to have more coverage and less infrastructure device "anchors" in the system. However, the accuracy of the RF-based systems can vary from 10 cm up to 100 m, mostly depending on the different RF-based technology they use. Predominantly, low-cost RF-based localization systems use Ultra-Wideband (UWB), Bluetooth, IEEE 802.11 (WiFi) and IEEE 802.15.4.

- *UWB* is arguably the most precise RF-based technology used for indoor localization. It leverages the use of short pulses of sub-nanosecond duration with a large signal bandwidth of > 500 MHz, in the frequency range from 3.1 GHz to 10.6 GHz. These properties make the UWB signal less sensitive to multi-path effects, and allow the correct estimation of ToF, uniquely identifying the direct path of the signal [48]. Although its precision mainly depends on finding the first LoS path of the signal, UWB can also be used in NLoS scenarios if application requirements allow for a less precise localization accuracy. UWB technology has been present for over a decade in low-power personal area networks. It is recently included in some of the new smartphone devices which will make this technology more accessible. Recently, Apple launched a new tracking device on the market called AirTag [49]. This device combines UWB and Bluetooth technology for tracking, where UWB ranging and direction finding is available on the iPhone 11 or newer. In Section V-C, we present a hands-on evaluation of one of the most popular UWB platforms, the Decawave DWM1001.
- *Bluetooth* has emerged as a major candidate for indoor localization due to its low power consumption, especially Bluetooth Low Energy (BLE) [50]. Most portable devices such as smartphones are Bluetooth-enabled and represent a great commercial opportunity for tracking and positioning applications as well as proximity detection. Although Bluetooth was mainly developed as a standard for communication, multiple localization and proximity detection applications leverage the Bluetooth radio. As an example, the availability of Bluetooth was extremely important for developing contact tracing applications during the health crisis of COVID-19

pandemic in France. The contact tracing application TousAntiCovid uses Bluetooth with proximity based techniques to detect whether the user had a close contact with a contagious person [51]. Although the aforementioned pros like low-cost, low-power and accessibility are very promising, Bluetooth-based localization systems suffer from a limited accuracy. There are many commercial products like BLE beacons using RSS for proximity detection [52]. BLE beacons are broadly used in wireless sensor networks, indoor/outdoor positioning and other low-power IoT systems. As a part of the Bluetooth 5 core specification Bluetooth Mesh allows direct, dynamic connection between BLE beacons [53]. These networks provide low-power many-to-many communication capabilities and it can be found in localization applications such as: home and industrial automation, asset tracking and proximity detection. BLE beacons usually offer room-level accuracy, except when the system includes some Fingerprinting method to allow for better accuracy. This method requires more computational power, environment information and human labor. Moreover, multi-path fading means a small change in the environment such as a door being opened may require new fingerprints to be collected. On the other hand, some promising work was recently done on enabling ranging capabilities with BLE allowing for a meter-level precision. Link Labs introduced a firmware upgrade for enabling BLE ranging, called Bluetooth Xtreme Low Energy (XLE) [54]. They claim a meter-level accuracy in 3D space, with 5-7 years of the tag battery life, depending on the update rate. Recently, a different localization approach is offered with the emerging BLE Direction Finding feature, with some companies claiming to have obtained 10 cm localization accuracy in their BLE AoA RTLS solutions [55]. However, there are some constraints that the new BLE AoA estimation feature has, which will be presented in the Sections V-A and V-B.

- *WiFi* technology has similar constraints as Bluetooth when it comes to its localization capabilities. It was originally deployed for communication. WiFi is ubiquitous which makes it a great candidate for localization application and many studies has been conducted trying to reuse the existing WiFi infrastructure for the indoor localization. However, WiFi has a room level accuracy and not particularly low-power. Similar to Bluetooth, it could benefit from better accuracy if the localization solution includes Fingerprinting together with carefully selected algorithms [56]. There are upcoming WiFi standards that could be considered for future research in WiFi-based localization, 802.11ax and 802.11ah [57], [58]. The former operates on 2.4 GHz or 5 GHz frequency bands and allows high-throughput in high-density settings such as stadiums, corporate offices and shopping malls. The latter operates on sub 1 GHz license-exempt bands. It provides low-power long range communication capabilities suitable for large scale sensor networks, which could be important to consider when designing localization systems that cover large areas.
- The *IEEE 802.15.4* standard defines the physical and MAC layer for low-cost, low-rate wireless personal area networks. It operates in license-free frequency bands at sub 1 GHz and 2.4 GHz. It is widely used in Wireless Sensor Networks (WSN) to transport sensor data and actuator commands. The standard defines the function of measuring the received signal power in the form of Received Signal Strength Indicator (RSSI). Therefore, a sink node can estimate the location of an end device inside the network using statistical models based on measured signal propagation characteristics [59]. The IEEE 802.15.4 standard is the core element of many wireless network technologies such as: ZigBee, Wireless HART, 6TiSCH and Z-Wave [60]–[63]. These technologies motivated new research in the indoor localization field, to expand device capabilities to add location information inside the WSN. ZigBee technology adds the routing and networking functionality on top of IEEE 802.15.4. This allows devices to function as routers, expanding the range of communication. Because ZigBee uses IEEE 802.15.4 as a baseline standard it also has the ability to obtain RSSI information [64]. Cheon *et al.* [65] demonstrates the ToA estimation using ZigBee devices which could enable ToF-based positioning systems in WSN. Industrial WSN solutions like SmartMesh IP can benefit from device location estimation using RSSI. By employing similar techniques as with BLE beacons, low-power wireless mesh networks can provide a room-level localization accuracy [66]. Moreover, researchers in the indoor localization field could consider Z-Wave communication technology [67]. Z-Wave is mainly used by home automation systems to connect various smart devices and appliances. Unlike ZigBee which operates in both sub 1 GHz and 2.4 GHz, Z-Wave devices operates only in license-free sub 1 GHz frequency band, in order to avoid interference from other technologies like WiFi. Devices that support this technology can form a mesh network with the limit of 232 connected devices.

C. ARCHITECTURE TYPES

When designing RTLS the researcher needs to carefully examine the application requirements. In order to tailor the system to match the use case, the appropriate architecture approach is needed. In this paper we differentiate two architectures: inside/out and outside/in.

An *inside/out* approach allows the mobile device to know its position relative to the localization infrastructure. Usually, this approach requires the computation of the location on the mobile device, given the necessary data from the infrastructure. In the case of the localization of user/smartphone devices, computational power of these devices is not very limited and the designer could implement "heavy" algorithms for localization. For resource constrained devices such as low-cost and small form-factor robots, this can be computationally challenging. In this case, the designer needs to carefully select the appropriate localization algorithm which suits the limited computational power of the device. This approach is primarily used for navigation of the mobile device. However, the end device can also report its location back to the localization system to display its position for the tracking purposes.

An *outside/in* approach is typically used in tracking applications, where the localization system tracks the mobile device and provides different services according to the application requirements. In this architecture, the localization infrastructure collects the necessary information from the mobile device. The location of the mobile device is then computed by the localization system. This architecture allows the tracking of a large number of devices, with extended battery life of the mobile device. Inside/out and outside/in architecture approaches are depicted
in Fig. 4.

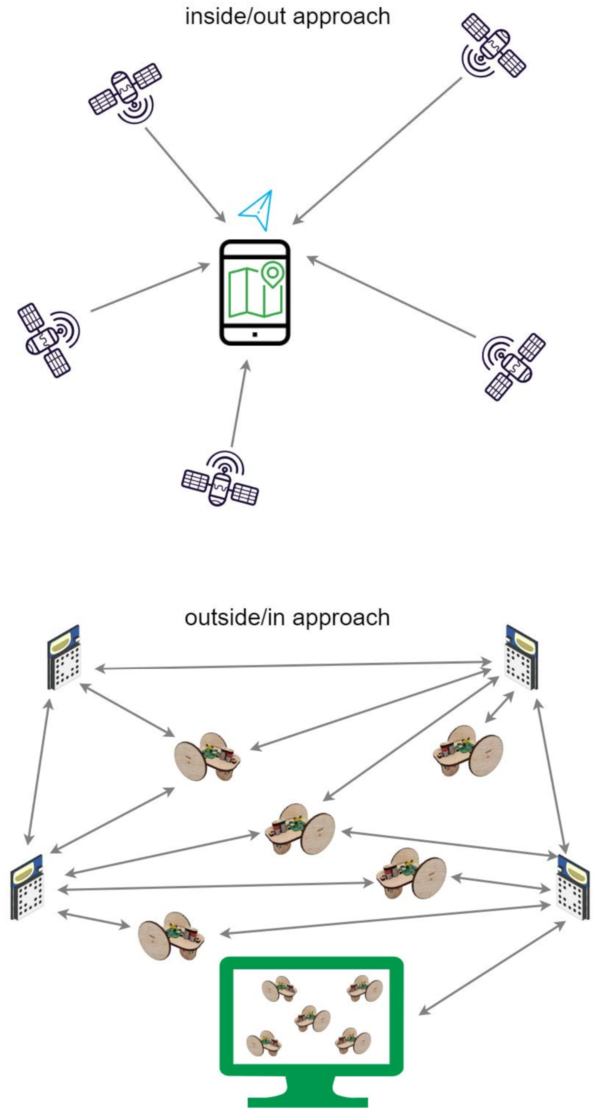


FIGURE 4. Localization architecture approaches: inside/out (top) and outside/in (bottom).

III. TAXONOMY - CLASSIFICATION CRITERIA

In this section, we propose classification criteria for the recent academic research on indoor localization. We introduce five different criteria: Line of Sight (LoS) requirement, accuracy, update rate, battery life and cost. These criteria will allow us to classify the recent work on indoor localization in academia, and better understand what the constraints of their solutions are with respect to the metrics mentioned.

A. LINE OF SIGHT (LoS) REQUIREMENT

The LoS requirement is probably the biggest constraint for the light-based and the sound-based localization systems. Given their nature, signals can't penetrate walls and obstacles and require a direct LoS to work properly. For the RF-based systems, LoS is also favorable but the NLoS ranging could also be exploited [68]. Even though the LoS requirement is mainly determined by the type of fundamental technology used, it can be also required by an application.

B. ACCURACY

The precise accuracy of a localization system is typically the main requirement of any localization application. As one of the most important characteristics of the localization system, good accuracy is needed for the tracking and navigation of a user/device in a certain environment. The accuracy of a localization system depends mainly on the technology constraints, as well as on the careful selection of localization algorithms to estimate the position of the mobile device. Some light-based technologies offer millimeter-level localization accuracy, while some RF-based technologies like Low-Power Wide-Area Network (LPWAN) [69] offer 100 m localization accuracy. For evaluating the localization accuracy authors usually employ schemes such as: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Maximum Error (ME) and Mean Absolute Deviation (MAD) [70]–[72]. Although different applications have different accuracy requirements, in this survey we will treat a sub-decimeter level accuracy as the precise localization.

C. UPDATE RATE

RTLS systems typically require fast location updates without significant delays. Depending on the application this could be of crucial importance. In industrial monitoring applications, fast location updates from the autonomous robots or conveyor belts are needed to ensure safe operation. Unlike industrial environments, asset location for tools or medical equipment is usually reported when the asset moves from its original position. Even in these applications, a periodic location update is needed in order to ensure that the asset is in its right position.

D. BATTERY LIFE

Energy efficiency is one of the crucial features for any localization system. The user should be able to use the system without needing frequent battery replacement on the devices that need to be located. Many systems offer the possibility of rechargeable batteries on the mobile devices, but this is not convenient for most tracking applications that need the system to run continuously. In the best case scenario, the localization system needs to offer several years of battery life, where the careful trade-off should be made between localization battery life and update rate, according to the application requirements.

E. COST

An important aspect of any localization system is its cost. Nowadays, many semiconductor companies offer a localization-enabled low-power chipsets, that could be integrated in everyday devices. The exploitation of connectivity and sensing together with the localization possibilities inside the single low-cost device opens up a wide range of new applications.

IV. RECENT ACADEMIC RESEARCH ON INDOOR LOCALIZATION

This section surveys recent academic research on Indoor Localization. The works are grouped by fundamental technology used: light-based IV-A, sound-based IV-B, RF-based IV-C.

A. LIGHT BASED LOCALIZATION

Aswin *et al.* [73] present a localization system using visible light as its fundamental technology. The LEDs transmit Manchester encoded messages previously stored in an MSP430 microcontroller. For calculating the receiver's position, the authors use four synchronized transmitters to transmit in a TDMA scheme. The communication data rate is set to 20 kbps due to limitations of the receiver. Localization information is obtained by measuring the RSS from all four transmitters. Experimental validation is done by having a labeled area below the transmitter as a 4×4 matrix (87 cm x 87 cm), with 1.6 m between the transmitters and receiver. The system needs to be trained several times by putting the receiver in each matrix cell to record the RSS of the transmitters. Position is then calculated by the probability of occurrence. The authors indicate this system has sub 1 m accuracy in experimental conditions. They also provide an image processing based localization method using a camera to localize the transmitters, which is not integrated in the prototype of the system.

Kilberg *et al.* [74] present the localization of the quadrotor using bearing estimations from deployed nodes at known positions. The quadrotor is equipped with a planar laser, a 9-axis IMU, a 802.15.4 radio, and an optical flow deck and z-ranging infrared sensor for velocity and altitude measurements. Deployed motes are equipped with an IEEE 802.15.4 radio and a photodiode that receives the IR light from the planar laser on the quadrotor. The system is using OpenWSN TSCH as a synchronized time base. The lighthouse quadrotor rotates while recording its heading-timestamp information. Anchor node detect the laser sweep and record the network-synchronized timestamp. The lighthouse robot periodically broadcasts its timestamp-orientation mapping to anchor nodes. Anchor nodes use the received timestamp-orientation broadcasts and previously stored timestamps from the laser sweep to calculate their bearing relative to the quadrotor. Each anchor node then sends that relative bearing back to the lighthouse quadrotor, which uses it to localize itself. The authors use the Extended Kalman Filter (EKF) on the Crazyflie for state estimations. The experiment is performed in a motion capture room using the OptiTrack system for capturing ground truth information with sub-milimeter accuracy. The reported RMSE for the position on the x axis is 0.57 m, the RMSE for the position on the y axis is 0.39 m. This error is measured after the filter converged (after 175 s). Over the duration of the experiment, the gyroscope drift accumulated to 20 degrees of error near the end of the quadrotor's flight. The pose was estimated using the stock Crazyflie EKF algorithm, which relies on the gyroscope measurement data. The measured bearing error bias (mean error) is 19.5 °, with a standard deviation of 24.7 °. The authors report that this error is larger than expected, and that a likely cause of error is the timing error introduced by the firmware interface between the wireless sensor node performing measurements and the Crazyflie. This system could also be used with nodes with an unknown position.

Kilberg *et al.* [75] present a lighthouse-based localization system for localizing a crystal-free single-chip micro mote, called SCuM. Lighthouse localization insures that the form factor of the SCuM chip is not changing by using its optical receiver not only for programming but also for receiving IR pulses from a lighthouse base station. The SCuM chip computes its azimuth and elevation relative to the base station. The authors use two base stations in order to determine the 3D position of the mote using a Direct Linear Transformation and triangulation. SCuM reports its azimuth and elevation to the OpenMote board connected to the PC. The position is calculated on the PC. The system is evaluated using the OptiTrack sub-millimeter tracking system as ground truth. When clear outliers are removed in post-processing (errors bigger than 10 °) the 3D triangulated tracking data gives the mean absolute error of 1.54 cm, 1.50 cm, and 5.1 cm for the x, y, and z axis, respectively.

Campos *et al.* [31] describe the use of the lighthouse localization with EKF in the conveyor belt industrial application. The transmitting node is located on a conveyor belt containing an open-source wireless sensor mote MIMSY [76] and an optical receiver module for receiving IR laser sweep from the lighthouse. When the node enters a predefined unsafe zone on one side of the conveyor belt, a message is sent to the receiver circuit which reverses the DC motors. The process is repeated when the cart reaches the unsafe zone on the other side. The lighthouse base station is located 3 m from the cart. The system exhibits as less than 1 mm precision over 1 M azimuth samples. The update rate for the EKF is 1 kHz, the same as the sample rate of the accelerometer. Results show that median overshoot (after entering the unsafe zone) is 9.9 mm for lighthouse only, and 1.1 mm when using EKF. The standard deviation for lighthouse only is 10.9 mm and 0.8 mm for the EKF. The median latency of the lighthouse localization only is 26.7 ms, 3 ms for the EKF. The use of an EKF and accelerometer allows the position estimation in NLoS conditions when there is an occlusion. The authors report that, when no part of the conveyor belt is occluded from the lighthouse base station's IR sweeps, the position estimate at the unsafe zone boundaries has a median standard deviation of 0.109 mm. In the case where half of the conveyor belt is occluded from the base station, the EKF reports a median position estimate standard deviation at the occluded boundary of 0.875 mm.

Yan *et al.* [77] describe CurveLight, IR light-based indoor localization solution. In the proposed system the transmitter consists of an IR LED, covered with a hemispherical shade that rotates, and a receiver that detects the light signal with a light sensor. The key element of the system design is a set of curves that define different regions on the shade that covers the transmitter. The shade rotates at 1200 revolutions per minute (RPM) and it is mounted on a ceiling at a known height, with LED flashing at 22 KHz rate. When the shade is rotating the transmitter generates a unique light signal, for each part of the area below the transmitter, due to the curved design of the shade. The transparent regions of the shade allow the light to pass without intensity loss and translucent regions that reduce the intensity of the IR. The receiver then decodes the light signal and calculates its angle in respect to North and radius because different radius corresponds to a different length of the gray arc (curved region with lower light intensity). The KF is then used to further improve the localization accuracy. Authors test the proposed system in indoor environment and production deployments. In the indoor environment the system achieves 2-3 cm average location error with an update rate of localization of 36 Hz. In case of a real-world deployment such as autonomous car parking system authors report the mean localization error of 3.5 cm.

B. SOUND BASED LOCALIZATION

Qi *et al.* [78] present a localization system based on ultrasound ToF measurements. The system consists of a server, multiple sensor nodes (anchors), and mobile robots that need to be localized. Each sensor node has two radio chips, a CC3200 for communication, a CC2500 for synchronization. The Least Squares Method is used to detect the envelope of the ultrasound signal. The authors report a 1 us synchronization error between nodes, where only two nodes are exchanging messages The reported mean distance error in the experiment is 0.6 mm for 1 m distance and 1.4 mm for 3 m distance between devices, in LoS conditions.

Esslinger *et al.* [79] present three optimization approaches for improving ultrasound ToF-based systems. The authors verify these optimization approaches by using mobile devices equipped with ultrasound transmitters and anchor devices equipped with ultrasound receivers. Mobile and anchor devices are also equipped with IR photodiodes used for time synchronization. The prototype allows tracking of multiple objects simultaneously by applying virtually orthogonal Gold codes to the carrier signals in a Code Division Multiple Access (CDMA) environment with the capacity of 127 transmitter devices. Gold code sequences are statistically uncorrelated and allow the use of the same frequency, resulting in less interference and better utilization of the available bandwidth. It takes 63.5 ms to transmit the entire Gold code. As first optimization approach, the authors present the adoption circuit at transmitter and receiver, and report an increase in 3 dB bandwidth by a factor of 7.2 and 12.2, respectively. The median distance measurement error is −4.18 cm without the adaption circuit, at 5.0 m. Applying the adaption circuit reduces the median error to 0.83 cm. In second optimization approach the authors present two mitigation strategies for reducing these spectral leakage effects caused by ADC sampling. Without any spectral leakage mitigation, the maximum absolute distance measurement error is 21.2 mm. The authors examine two approaches to reduce spectral leakage: circular correlation with multiple replicas having a different phasing, and envelope calculation in the circular correlation. Both approaches reduce the maximum absolute distance measurement error by 66.5%. However, authors report that the envelope calculation by Hilbert transform reduces the computational effort compared to the usage of multiple replicas. Finally, the authors propose an efficient circular correlation computation on FPGA. The real-time implementation of circular cross correlation shows that the distance measurement deviates with a median of 1.25 mm and has a variance of 5.57 mm.

Rekhi *et al.* [80] propose CRADLE, which combines RF and acoustic localization for ranging of passive tags. The system consists of a reader and a tag. The reader is capable of transmitting/receiving RF signal and transmitting ultrasound signals. The tag is equipped with an ultrasonic transducer connected to the RF antenna. The reader transmits the RF signal at a certain frequency together with an ultrasound signal. The ultrasound signal reaches the tag's ultrasonic transducer and excites it. This varies the transducer's capacitance and modulates the load of the tag's RF antenna. This creates sidebands which are then detected by the reader in the re-radiated RF spectrum. By demodulating the RF signal, the reader can extract the time when the passive tag received the ultrasound pulse. The reader computes the distance to the tag using the time it took for the ultrasound pulse to reach the tag. The tag's transducer is a precharged capacitive micromachined ultrasonic transducer (CMUT). The tag is completely passive and doesn't require battery power or energy harvesting for normal operation. The proof-of-concept of this system was tested in the outdoor environment with the distance from 1 to 6 m between the tag and the reader. The authors report a sub-decimeter level ranging accuracy, except at 2 m distance between devices where the error was above 10 cm. A possible application is lower cost motion capture systems. The future work outlined includes further miniaturization of the tags, enabling the tag's instantaneous velocity calculation using Doppler effect and making tags more isotropic.

C. RF BASED LOCALIZATION

Nandakumar *et al.* [81] present the localization of a backscatter tag with ultra small form factor that is able to run for 5-10 years on a coin cell battery. The tag can communicate at three frequencies: 900 MHz, 2.4 GHz, 5 GHz. The proposed approach is to use Chrip Spread Spectrum (CSS) where the Access Point AP sends chirps on three frequency bands. The tag offsets the signal and backscatters it to the AP, which extracts the range information from the phase of the signal. The tag is designed using off-the-shelf components (uC, RF switch…). The AP is designed using multiple software defined radios configured as transceivers. The authors use Non-Linear Least Squares to compute the 3D location. Multiple experiments are conducted to verify the accuracy of the localization, both in a lab setting and in real-world deployments in houses and hospitals. The localization error varies from 2 cm to 145 cm at distances from 1 m to the maximum 60 m between the tag and the AP. Authors report good performance in NLoS conditions, with a localization error of 33 cm at 20 m distance. In the real-world single-story apartment deployment, this system achieves an accuracy of less than 30 cm. For two multi-story apartment deployments, the system achieves an accuracy of 60 cm and 1.2 m. When deployed in a hospital, the mean accuracy is 35.12 cm across all locations, with localization accuracy being proportional to the distance. The system can support multiple tags by having each tag shift the signal by different frequencies.

Ahmad *et al.* [82] present a localization system for passive backscatter tag-to-tag networks. Most backscatter tags utilize active receivers, whereas in the passive tag networks the tags are able to communicate by backscattering the signal between them. Communication between the passive tags can only exist in the presence of the external excitation signal. In this work authors develop a phase-based technique to perform ranging between the two passive tags. The ranging estimation is performed as a two-step process, estimating the amplitude and the phase of the signal and then extracting the range information from the signal's phase. The passive tag consists of a dipole antenna, 10-channel RF switch as a backscatter modulator, controlled by a microcontroller, a passive envelope detector demodulator and an 16 bit 1 Mbps ADC. The tag also contains USB interface and SD card for data collection. For evaluating the performance of their solutions authors use RF signal generator as the exciter to provide the RF signal to passive tags, operating at 915 MHz. The tags are positioned on a rail, at 1.5 m distance from the exciter antenna. Authors estimate the channel phase for tag-to-tag distances up to 2 m, repeating measurements 100 times at each distance. Authors report very small variations in phase within a few degrees with median ranging error of <1 cm. In order to evaluate localization performance authors propose the iterative likelihood-based technique, to extract exact the distance from the "wrapped" range estimation, due to the phase wraparound every 2π. Authors report a median localization error of <1 cm and the 90-percentile accuracy of <1 cm.

Yang *et al.* [46] use WiFi APs with multiple antennas as anchors in their indoor positioning solution. They estimate the tag's position through a combination of ToA with AoA. The mobile tag is a WiFi-enabled device with a single antenna, and can be a smartphone or a tablet. For measuring ToA, the WiFi AP sends multiples of the same predefined message to overcome the width constraints of the WiFi bandwidth. The signal reconstruction relies on finding the sample of a message that is closest to the arrival signal. For measuring the AoA, the mobile phone sends multiple messages toward the WiFi AP, where the AoA is measured by using channel estimation technique, taking advantage of the AP multiple antennas. In this approach, the WiFi AP acts as the initiator and sends the bursts of messages to the receiver (smartphone). After it receives the signal back from the smartphone, the AP calculates the ToF and AoA. The proposed solution is verified through simulation, where authors assume the following: when using only one AP the hybrid technique ToA/AoA is used, otherwise only AoA is calculated and position is obtained with triangulation. The authors consider a scenario where the SNR is 20 dB, and the WiFi AP's maximal indoor communication distance is 50 m. Using 10 predefined messages, a single WiFi AP can achieve 2.2 m and 1 m positioning range for 20 MHz and 40 MHz bandwidth, respectively. With multiple WiFi APs, the position range is 2.2 m and 0.5 m, respectively.

Yu *et al.* [83] introduce a localization system that uses the inertial sensors built into a smartphone together with the WiFi Fine Time Measurement (FTM) protocol and RSSI to track pedestrians in an indoor environment. The authors present the use of an Adaptive Extended Kalman filter (AEKF) to fuse triaxial data acquired from the accelerometer, gyroscope, and magnetometer to compute the pedestrian's real-time speed and heading information. This work combines the RSSI and RTT of the signals acquired from the local WiFi APs to allow more accurate WiFi ranging and proximity detection. The results of proximity detection are used to provide the absolute altitude reference to the barometer-based altitude calculation. Based on the results of the AEKF, the WiFi ranging, and the proximity detection, a real-time Unscented Particle Filter (UPF) is applied to fuse all these results. The sampling rate of the built-in sensors is 100 Hz and 4 Hz for the WiFi FTM. The real-time location update rate is 4 Hz. The heading calculated by the gyroscope drifts by about 30° after walking for around 20 min, while the fused heading drifts by only 4°. The fused RTT and RSSI gives the WiFi AP-based landmark detection errors in range from 0.25 m to 0.64 m, with a median error of 0.4 m. The 2D positioning performance is given with

CDF where the positioning error within 1.11 m at 67.5%. The altitude error is within 0.28 m at 67.5%.

Alletto *et al.* [84] design a localization assisted interactive guide to a smart museum environment. It has three main components: a localization service, an image processing function and a cloud-based processing center. For localization, the authors use BLE beacons pre-deployed in each room of the museum, providing room-level accuracy. The smartphone-like device the visitor carries receives frames from the beacons and uses their RSSI to determine the visitor's location in the museum. This information is then passed to the processing center to be used by different services. This room-level information helps speeding up computation time and saves battery power as the images taken from the wearable device are compared only to the dataset of the artwork located in that particular room. The localization system also serves to detect the number of visitors in front of the artwork. If the number of visitors is smaller than a defined threshold the processing center sends the audio information about the artwork. Otherwise, the processing center provides the relevant artwork information to the interactive wall inside the room. As a localization part of the real experiment performed in the museum authors consider two scenarios. In the first scenario the BLE infrastructure devices are placed in NLoS, on the wall separating two rooms. In the second scenario the BLE devices are placed in LoS at 5 m from the separating door. Results show that the localization estimation was optimal in the first scenario, with a wearable device located at three different positions, at 0.5 m, 1 m and 3 m from the separating door. For the second scenario the results show lower localization probability when the wearable device is placed closer to the separating door.

Faragher *et al.* [85] evaluate BLE fingerprinting with static BLE beacons located at known locations, using two approaches: single point position and tracking. Three advertisement BLE channels are used to gather RSSI information. These channels are associated with different gains and multipath effects, due to their narrow width and wide spacing. The authors use iPhone's iOS 7 or above, which indicates on which channel the message is received. The positioning algorithm consists of fingerprinting, map construction and position computation. The fingerprinting approach is evaluated by deploying 19 beacons in a 600 m^2 building floor, and measuring the RSSI to the beacons. At first BLE beacons transmit at 50 Hz at 0 dBm. The iPhone is used to log the BLE beacons. In parallel, an Android 4.4.2 device gathers the RSSI of the WiFi signal received from three APs. The localization is compared to ground truth gathered using an "Active Bat" system [86] which offers 3 cm accuracy, synchronized using a Network Time Protocol (NTP) server. The update rate of 10 Hz was found to be optimal, giving similar results compared to higher update rates. The best performance is achieved when 8-10 beacons are used per fingerprint. Lowering the transmit power to -15 dBm still provided good coverage for a reasonably low number of beacons. Authors report that their deployment of one beacon per 30 m2 gave accuracies of < 2.5 m 95% of the time. Lowering the density to one beacon per 100 m2 degraded gives accuracy of < 5.5 m.

Zhang *et al.* [47] use BLE RSSI fingerprint for indoor localization. In the offline phase the Motiosens UWB sensors together with the BLE beacons are used to construct the fingerprints. The testing environment is a room equipped with 12 BLE beacons and 8 UWB anchors. The beacons send advertisement packets every 350 ms with -4 dBm transmit power. All anchors (BLE and UWB) are 1.5 m from the floor. The data is collected from the BLE scanner and the UWB tag every second and uploaded in the location server. The UWB localization accuracy is tested with a tag located on the tripod (perfect LOS) and a person carrying a tag. Authors describe the latter as real conditions, but no other obstacle is put in the open space. The mean error for the tripod configuration is 0.039m. When a person is carrying the tag the error is less than 0.521m. To estimate the location through fingerprints authors use Machine Learning algorithms: k-Nearest Neighbor (KNN) and Gradient Boosting Decision Tree (GBDT). The system is trained with 80 % of the fingerprints collected. Authors validate the accuracy of the system on the remaining 20 %. The results show the mean distance error for different algorithms: Basic geometry - 2.83 m, KNN - 0.72 m, GDBD - 1.27 m, Random Forest - 0.85 m.

Khan *et al.* [87] evaluate the use of Machine Learning techniques and signal processing in order to improve the performance of Bluetooth AoA estimation. Authors propose a method of combining MUSIC algorithm with regression models including Gaussian Process (GP), Neural Network (NN), and Regression Tree (RT) in order to perform AoA estimation. For the machine learning model authors used 75 % of the data to train the model and 25 % for test the system. Authors are evaluating the proposed approach with simulations and real measurements, where the authors don't mention which commercial devices they use for real AoA measurements. The simulation results show that for 30 dB SNR when the multi-path effects and elevation angle are low the azimuth estimation was 20 % better for NN than the baseline MUSIC algorithm and 50 % better in case of RT and GS. For the SNR of 30 dB and with elevation increasing the NN and the GS outperforms the baseline MUSIC. For this case the RT had comparable results to the MUSIC algorithm. In the case of SNR between 0 dB and 30 dB the estimation improved for both the NN and the GP approach. The real measurements give the Mean Absolute Error in AoA estimation as follows: MUSIC - more than 9°, NN 3.5°, GP 3°, RT 3.5°. Measurements are done with an elevation angle from 0° to $-20°$. Authors state that the GP approach gives the best results but has the computational time of 40 ms. This is a lot slower compared to NN's 7.8 ms to process a single test set of 1530 samples. The RT approach has the fastest computational time of 1.4 ms but its performance degrades with higher elevation angle and lower SNR.

Hajiakhondi *et al.* [88] describe the signal processing methods to minimize the error of AoA estimation in BLE.

Proposed processing framework is done in three steps. First, Nonlinear Least Squares (NLS) curve fitting is proposed for reducing the noise after the I/Q signals are collected and is applied to raw data. All data is fitted in sinusoidal curve. Second, authors use Kalman Filter (KF) for smoothing the phase and frequency variations on different samples. These variations cause big errors when estimating the angle and happen due to the phase shift of oscillator in both the transmitter and the receiver sides as well as in the switching elements. Third, Gaussian Filter (GF) is implemented for eliminating WiFi interference on the BLE channels causing angle calculation error. A constant angle offset is calculated for all 37 BLE data channels in order to improve the angle estimation. Authors use Texas Instruments RTLS development kit with BOOSTXL-AOA antenna array for the experimental evaluation. The AoA is estimated in the area from $-90°$ to $90°$. After processing the raw data the results show that from $-60°$ to $60°$ this method gives the errors of less than $10°$. Errors grow significantly when moving towards $-90°$ and $90°$ and the AoA estimation are almost random.

Jondhale *et al.* [89] present the indoor tracking solution based on Generalized Regression Neural Network (GRNN). Authors further use KF and UKF in order to improve localization accuracy. For evaluation their approach authors utilize off the shelf BLE devices as anchors which send beacons to a smartphone that tracking person carry. Collected RSSI are then transferred to a central computer which computes the calculation of 2D position using proposed algorithms. Authors compare traditional trilateration method with GRNN, as well as trilateration + KF/UHF and GRNN + KF/UHF. The testing site is a lab area 10 m x 15 m equipped with four anchors (Cypress CYBLE-022001-00 BLE nodes) and smartphone (Motorola G4 Plus). Authors train proposed tracking system with the set of 70 RSSI samples and validate their approach with 35 RSSI samples. The accuracy of the system is evaluated using average localization error and RMSE. In the first phase of the research evaluation authors compare traditional trilateration to GRNN approach. Authors report the Average RMSE below 1 m in case of GRNN algorithm. The Average Localization Error and the Average RMSE is reduced by 59 % and 48 % with the GRNN approach compared to trilateration. In the second phase of evaluation authors compare trilateration + KF/UHF and GRNN + KF/UHF. Authors report that the fusion of GRNN and KF approach can provide very high tracking accuracy of centimeter scale. The Average Localization Error and the Average RMSE is lowest for the GRNN + UKF algorithm and is 6 cm and 8 cm, respectively.

Jondhale *et al.* [90] evaluate the use of Support Vector Regression (SVR) in RSSI-based indoor positioning systems. Authors compare the proposed SVR scheme to traditional trilateration and GRNN. Furthermore, authors fuse SVR scheme with KF in order to improve the accuracy. For evaluating their approach authors use simulations, where they track a mobile device using six anchor nodes deployed in a 100 m x 100 m. The proposed SVR localization model was trained with 120 input vectors, each containing three RSSI measurements from three anchors and 120 corresponding 2D positions of the mobile target. Authors use Log-Normal Shadowing Model (LNSM) to generate RSSI values and perform simulations in two phases. In phase I, SVR localization is compared to traditional trilateration and GRNN. Comparing to trilateration results simulations show an average RMSE decreased by 52 % and 62 % and average localization error decreased by 51 % and 66 % using GRNN and SVR respectively, In phase II authors compare SVR method to SVR fused with KF. The average RMSE and average localization error with the SVR + KF scheme decreased by approximately 95 % and 79 %, with average RMSE of 26 cm and average localization error of 85 cm for 2D localization.

Horvath *et al.* [91] present the UWB TWR algorithm that uses the passive approach in two-way ranging together with double-sided exchange of messages between anchors and tags. This method could be suitable for applications where extended battery life. In passive TWR, if anchor 2, which does not take part in the process of two-way ranging between the anchor 1 and the tag, can receive their messages then the distance between anchor 2 and the tag can be determined as well. This way the number of ranging messages can be reduced to only two messages instead of communicating with all anchors one by one. The authors present a mathematical analysis of the ranging error propagation of the TWR, Passive TWR, Extended TWR and Passive Extended TWR. Passive TWR is explained as a good solution to avoid message exchange with every anchor and it is a good way to extend battery life. Passive Extended TWR improves the accuracy and together with the message number reduction allows for a smaller energy consumption. The proposed method is therefore a good candidate for battery constrained ranging applications. However, this paper doesn't present a simulation or implementation of the proposed Passive Extended TWR.

Bonafini *et al.* [92] present the solution for positioning in order of tenth of a meter and time synchronization in order of milliseconds using the UWB Decawave DWM1001 modules. Authors are exploiting UWB short pulses and accurate ToA estimation to create time synchronization for the end nodes. The experiment is performed using DWM1001-DEV boards with DRTLS software provided by Decawave. With this software UWB anchors and tags form a network where they communicate by Time Division Multiple Access (TDMA) as a MAC layer. Here the superframe carries all the information about anchors and performed ranging. The ranging algorithm used in this paper is SDS-TWR. Authors want to exploit the *RX_SFD* signal that is generated at the reception of the beacon sent by the network coordinator anchor (BCN0), record the time when uC detected this signal and compare it's internal clock drift to the network coordinator as a reference time. Presented results show the time reference from UWB nodes of a DRTLS network with a maximum jitter of 3.3 us and a standard deviation of 0.7 us.

Kolakowski *et al.* [93] present cooperative localization using TDoA and TWR fused together through EKF. In the presented approach the tags transmit the UWB packet to the anchors for TDoA calculation and are also capable of performing TWR with other tags. Tags send TWR results to the anchors over the UWB interface. Anchors measure time of packet arrivals and transmit all gathered results to the system controller. The proposed approach was tested in Matlab simulation and experimentally. The algorithms precision was simulated by comparing the Circular Error Probability (CEP) for TDoA and the cooperative method. CEP is calculated for 68 % of the derived results. Comparing to just TDoA, the use of cooperative algorithm improved the quality of the calculated tag positions using the CEP metric. Authors report the highest CEP value for combining TDoA and TWR system is close to 45 cm. In the experimental evaluation authors use a TDoA-based positioning system with 6 anchors and 1 reference anchor, and the EVK1000 evaluation kit for TWR measurements. The reference anchor in TDoA positioning system is equipped with TCXO used as a reference clock for synchronization. Similar to the simulation, when looking at the CEP metric for 68 % of the measurements taken, results show that the positioning precision has been strongly improved with cooperative approach compared to just TDoA. However, the use of cooperative algorithm did not improve positioning accuracy which was worse than by just using TDoA positioning system alone. Authors claim that such effect can be prevented by employing an algorithm for selecting the best set of nodes to range with.

Pannuto *et al.* [94] present a new design of UWB tags and anchors for providing decimeter level accuracy. The proposed solution implements the bandstiching technique for signal reconstruction at the receiver's side instead of using fast ADC and real time sampling. The developed solution is evaluated in the use case of tracking a micro quadrotor, with a surface area of 250 m2. Authors use TDoA technique, where the anchors are synchronized between each other, and tag transmits UWB pulse continuously. Authors have designed custom tags and anchors from available commercial electronic parts. They give a detailed description of how the tag and anchor are designed and built. The tag is made of a 3.9 x 1.5 cm PCB with a 2.4 x 2.2 cm UWB antenna. The entire tag fits within a 3.9 × 2.2 × 0.2 cm bounding box or about 1.5 cm3. The tag weighs 3 g and draws 75 mW of power. The anchors consist of a central 6.7 × 5.8 cm PCB with three 2.4 × 2.2 cm UWB antennas mounted co-planar at 120° offsets to avoid cross polarization. Each anchor needs a dedicated USRP1 for signal processing and data transport to a computer, where one USRP1 can service up to two anchors. The use of commercial off the shelf SDRs add significantly to the cost of the anchors. Authors report that one 3.2 GHz Xeon core can solve a position estimate in 231 ms and that at least five parallel cores are required to maintain a 19 Hz update rate. Harmonium achieves a median of 14 cm error with a 90th-percentile error of 31 cm and median precision of 9 cm, having motion capture as a ground truth with millimeter precision. Authors mention that they didn't compare this system to the Decawave UWB solution.

Chantaweesomboon *et al.* [95] present the hands-on evaluation of the TREK1000 RTLS kit provided by Decawave. Multiple scenarios were evaluated with configurations using three and four anchors. RTLS algorithm uses the trilateration method and TWR is the technique applied between tag and anchors. TREK1000 allows for a change in RF settings and the use of 4 different modes: L2 - channel 2 with 110 kbps data rate, L5 - channel 5 with 110 kbps data rate, S2 - channel 2 with 6.8 Mbps data rate and L5 - channel 5 with 6.8 Mbps data rate. Slow position update rate was reported when using the long frame L2 and L5 modes. Indoor performance evaluation for 2D localization show around 50 % of the data reporting 50 cm error or less, with no impact on accuracy having the 4th anchor included for 2D localization. For 3D localization in the indoor scenario results show worse performance with 3 m error for 50 % of samples, also with no significant difference between 3 or 4 anchors Outdoor 2D localization error was sub 70 cm for 100 % samples, sub 10 cm for around 50 % of the measurement samples. Authors report that the S2 mode provided the estimated locations with the smallest distance error. As for the indoor environment, there was no significant difference when using the additional fourth anchor for 2D outdoor localization. In the outdoor setup three out of four anchors were placed at height of 130 cm and the forth anchor was placed at height of 100 cm. 3D outdoor localization performance is evaluated with tag set on two different heights, 110 cm and 150 cm. Authors report less than 3 m of error on 100 % measurement samples in the case where the tag is at 110 cm height, located between two planes covered by the anchors. When the tag is positioned at 150 cm (above all anchors) position estimation is worse with less than 4 m error on 100 % of the measurement samples. The authors point that the anchors should be in the boundaries of the localization area. Also, at least two pairs of anchors should be in LoS and located 2-3 m above the ground. Finally, authors conclude that not all anchors should be in the same plane, with one anchor located far from the plane of first three anchors in order to have better z axis estimation.

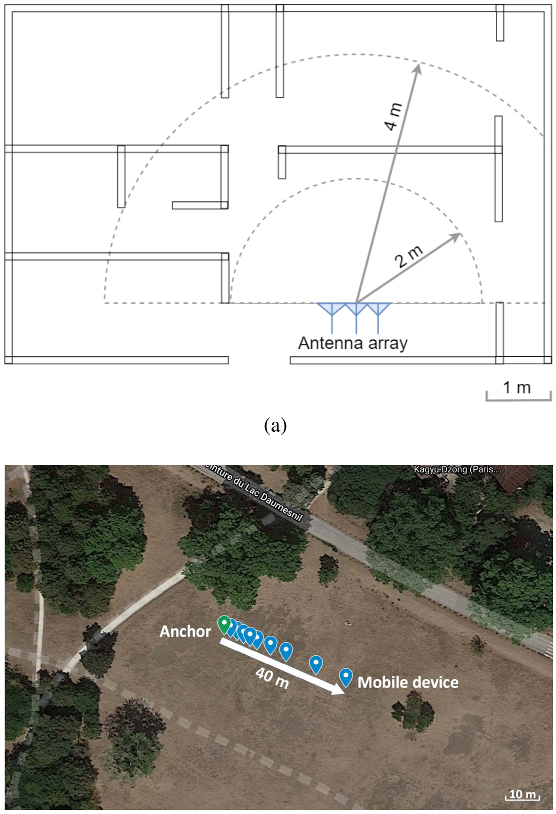
Kulmer *et al.* [96] present the work on UWB localization using a single anchor. Authors exploit the possibility of using multi-path propagation together with LOS signal to determine the tag's position. For this approach previous knowledge of the environment is needed to determine the strong multi-path components reflections. The evaluation of the proposed approach is done using the Pozyx off the shelf devices which include the DW1000 transciever ICs. To estimate the tag's position authors exploit the possibility of the position related information located in the Channel Impulse Response (CIR) measurements. The DW1000 IC is capable of returning the CIR value which makes it suitable for evaluating this approach. Position estimation is done at 100 different positions within 27 x 27 cm grid, where the moving tag is placed. Results show that with strong reflected signals with big Signal-to-Interference-plus-Noise-Ratio (SINR) the position error of both channels is decreased and the 90 %

limit of the CDF is reached within approximately 0.5 m of positioning error.

Barua *et al.* [97] give the evaluation of the UWB TWR distance measurements in an underground mine. The authors use TREK1000 evaluation kit from Decawave. Two scenarios are examined, LOS and NLOS, with distance between nodes up to 15m. In the NLOS scenario the first two meters were LOS due to the testing site "L shape" configuration. The measurements were performed using 4 different settings on two channels: L2 - channel 2 (4 GHz) with 110 kbps data rate, L5 - channel 5 (6.5 GHz) with 110 kbps data rate, S2 - channel 2 (4 GHz) with 6.8 Mbps data rate and L5 - channel 5 (6.5 GHz) with 6.8 Mbps data rate. In the LOS scenario the minimum RMSE of 20-30 cm has been observed for the L2 setting. The maximum RMSE for LoS up to 1 m for S5 setting. For the NLOS scenario the minimum RMSE of around 1.5 m has been reported for the L5 setting. Maximum RMSE for NLoS of up to 2 m is measured for the S2 operational mode.

Zhao *et al.* [98] propose a framework for improving UWB TDoA localization accuracy for recourse constrained mobile robots. The proposed framework tackles two challenges: the systematic bias caused by antenna radiation characteristics and outliers caused by NLoS and multi-path. The systematic bias is compensated with lightweight NN and outliers are handled with M-estimation based EKF. Authors partitioned the dataset into training, validation and testing using a 70/15/15 split. The proposed approach allows the real-time execution and is validated on-board a Crazyflie 2.0 nano-quadcopter. In this paper the quadcopter is equipped with IMU and UWB tag based on DW1000 IC. Test setup also include 8 UWB TDoA anchors and a motion capture system as a ground truth, installed a 7 m x 8 m x 3 m room. In this test setup M-estimation EKF-only is used as a baseline and is compared against the estimation enhanced NN, with and without the anchor orientation information. Authors report that proposed approach with NN bias compensation, considering the anchor orientation gives the best results. Results show an average of 42.09 % localization error reduction compared to the baseline, with approximately 0.14 m RMS localization error on-board a Crazyflie.

We present our classification criteria and recent academic papers on indoor localization in Table 1. We selected the thresholds for our classification to match our DotBot localization use case, introduced in Section I. First criteria in the table is the *LoS requirement*, i.e. if the localization system needs LoS to work. Then, we introduce *accuracy*, where we consider a < 10 cm accuracy as a precise localization. *Update rate* of the localization of at least 10 Hz is needed to match our use case. As low-power localization systems we consider those where the mobile device has > 1 year of *battery life*. According to our DotBot use case we consider a mobile device with the *cost* of < USD 20 to be low-cost. Finally, we discuss the results and lessons learned in Section VI.



(a)

(b)

FIGURE 5. AoA estimation (top) and UWB ranging (bottom) testing site.

V. HANDS-ON EVALUATION OF COMMERCIAL RTLS PRODUCTS

In addition to the survey of recent academic research on indoor localization given in Section IV, this article presents a series of hands-on evaluations of RF-based commercial products used for RTLS. We evaluate the performance of Bluetooth AoA and UWB commercial products.

The purpose of these experiments is to get a feel on how different localization technologies perform, with some insights into their capabilities and constraints. As this is not an in-depth comparison of commercial RTLS products, we perform fundamental experiments that allow future researchers to develop an intuition before choosing the right localization technology for their work. We obtain results with hardware, firmware and software provided by manufacturers as is, without additional work done to improve their performance.

We perform a hands-on evaluation of two AoA development kits, from Texas Instruments in Section V-A and Nordic Semiconductor in Section V-B, and one UWB development kit from Decawave in Section V-C. To conclude, we discuss lessons learned in Section VI.

A. TEXAS INSTRUMENTS AoA

Bluetooth direction finding was standardized in 2019 as a major feature of the Bluetooth 5.1 Core specification. This

TABLE 1. Classification of the recent academic research papers on indoor localization.

research paper	arch. approach	technique	technology	LoS	accuracy	upd. rate	bat. life	cost
Aswin et al. [73]	outside/in	RSS	visible light	yes	> 10 cm	?	?	< USD 20
Kilberg et al. [74]	outside/in	AoA	IR lighthouse	yes	> 10 cm	?	< 1 year	< USD 20
Kilberg et al. [75]	inside/out	AoA	IR lighthouse	yes	< 10 cm	?	> 1 year	< USD 20
Campos et al. [31]	inside/out	AoA	IR lighthouse	yes	< 10 cm	> 10 Hz	?	< USD 20
Yan et al. [77]	inside/out	AoA	IR	yes	< 10 cm	> 10 Hz	?	?
Qi et al. [78]	outside/in	ToF	ultrasound	yes	< 10 cm	?	< 1 year	> USD 20
Esslinger et al. [79]	outside/in	ToF	ultrasound	yes	< 10 cm	?	< 1 year	?
Rekhi et al. [80]	outside/in	ToF	RF/acoustic	yes	< 10 cm	?	> 1 year	< USD 20
Nandakumar et al. [81]	outside/in	PoA	backscatter	no	< 10 cm	?	> 1 year	< USD 20
Ahmad et al. [82]	outside/in	PoA	backscatter	yes	< 10 cm	?	> 1 year	< USD 20
Yang et al. [46]	outside/in	ToF/AoA	WiFi	no	> 10 cm	?	< 1 year	< USD 20
Yu et al. [83]	outside/in	ToF/RSS	WiFi	no	> 10 cm	< 10 Hz	< 1 year	< USD 20
Alletto et al. [84]	outside/in	RSS	Bluetooth	no	> 10 cm	?	< 1 year	> USD 20
Faragher et al. [85]	inside/out	RSS/Fingerprint	Bluetooth	no	> 10 cm	> 10 Hz	< 1 year	< USD 20
Zhang et al. [47]	outside/in	RSS/Fingerprint	Bluetooth	no	> 10 cm	?	?	?
Khan et al. [87]	outside/in	AoA	Bluetooth	yes	?	?	?	?
Hajiakhondi et al. [88]	outside/in	AoA	Bluetooth	yes	?	?	?	> USD 20
Jondhale et al. [89]	outside/in	RSS/GRNN	Bluetooth	no	< 10 cm	?	?	< USD 20
Jondhale et al. [90]	outside/in	RSS/SVR	?	no	> 10 cm	?	?	?
Horvath et al. [91]	?	ToF	UWB	no	?	?	?	?
Bonafini et al. [92]	outside/in	ToF	UWB	no	?	?	< 1 year	< USD 20
Kolakowski et al. [93]	outside/in	TDoA/ToF	UWB	no	> 10 cm	?	< 1 year	> USD 20
Pannuto et al. [94]	outside/in	TDoA	UWB	no	> 10 cm	> 10 Hz	< 1 year	< USD 20
Chantaweesomboon et al. [95]	outside/in	ToF	UWB	no	> 10 cm	> 10 Hz	< 1 year	> USD 20
Kulmer et al. [96]	outside/in	ToF	UWB	yes	> 10 cm	?	?	> USD 20
Barua et al. [97]	outside/in	ToF	UWB	no	> 10 cm	?	?	> USD 20
Zhao et al. [98]	inside/out	TDoA	UWB	yes	> 10 cm	> 10 Hz	< 1 year	< USD 20

new feature has encouraged semiconductor companies to invest in making SoCs capable of providing localization through AoA estimation. The new standard allows the development of commercial RTLS solutions, using Bluetooth AoA as its core technology [55].

Texas Instruments is one of the few semiconductor companies on the market that offers a commercial development kit together with an antenna array for evaluating AoA direction finding. The AoA development kit comprises the BOOSTXL-AOA kit and CC26 $\times$ 2R LaunchPad evaluation boards. The former consists of two orthogonal antenna arrays with three dipole antennas operating at 2.4 GHz (Fig. 6). Firmware and direction viewer software are also provided by Texas Instruments as a part of SimpleLink CC13 $\times$ 2-26$\times$2 SDK 4.30. The evaluation kit from Texas Instruments provides raw angle estimation without any filtering algorithm by default, which leaves the RTLS designer to chose the appropriate algorithm to improve performance when designing a localization system.

We verify AoA estimation using the Texas Instruments evaluation kit in a realistic scenario. The testing site is a two-bedroom apartment, with the antenna array positioned in the living room, allowing AoA estimation of the mobile device at 2 m distance (LoS) and 4 m distance (NLoS) from the antenna array center (Fig. 5(a)). In order to provide a realistic scenario, we perform the experiment in the presence of WiFi and multiple wireless devices such as smartphones and laptops. The testing site is such that the antenna is placed on the tripod, the mobile device in ''front'' of it, as shown in Fig. 7. At 2 m distance, we perform AoA estimation with a step of 10°. At 4 m distance, we measure the angle for a smaller number of measurement points, due to the size of the apartment. The position of the antenna array is 2.1 m above the apartment floor, with the mobile device located on the floor. We obtain the ground truth of the angle by attaching one end of a fishing wire to the center of the reference circle below the antenna array, and the other end of the wire to the mobile device. The reference circle contains the angles with 10°

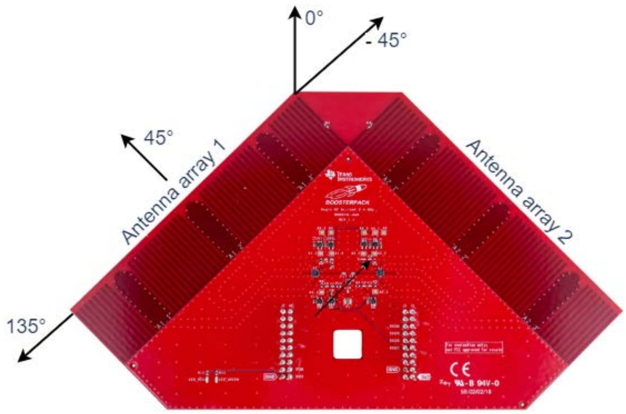


FIGURE 6. BOOSTXL-AOA antenna array from Texas Instruments.

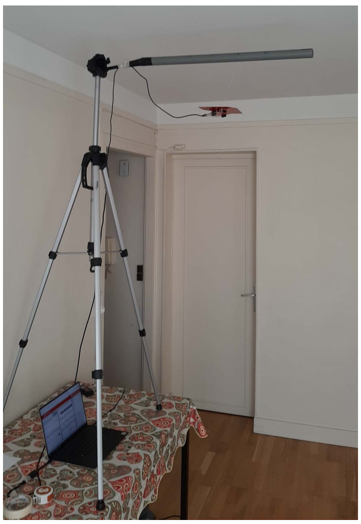


FIGURE 7. BOOSTXL-AOA angle of arrival estimation test setup.

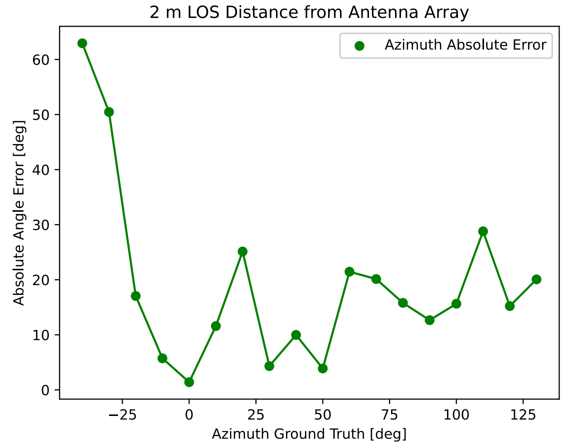


FIGURE 8. Absolute AoA estimation error with mobile device located at 2 m distance from the antenna array in LoS using BOOSTXL-AOA.

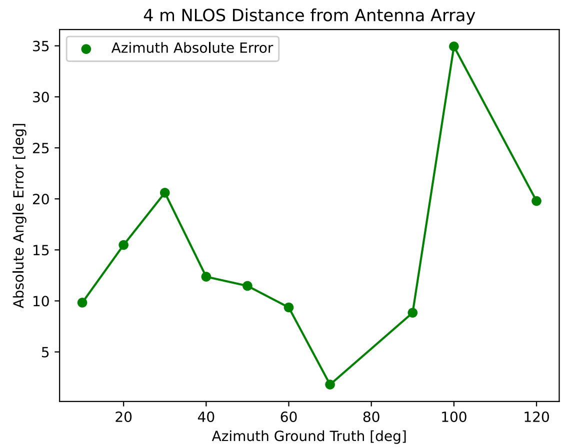


FIGURE 9. Absolute AoA estimation error with mobile device located at 4 m distance from the antenna array in NLoS using BOOSTXL-AOA.

steps, for measuring the ground truth. Distance is measured from the center of the reference circle to the antenna of the mobile device.

We perform AoA estimation using antenna array 1 on the BOOSTXL-AOA kit which covers angles from $-45°$ to $135°$ (Fig. 6). The antenna array has three dipole antennas positioned linearly. This allows only for the azimuth angle estimation. As mentioned before, default software for AoA estimation gives raw angle measurements; we obtain the azimuth angle at each measurement point by logging and averaging the results in a 30 s time window.

At 2 m distance from the antenna array with LoS (Fig. 8) the raw AoA estimations shows big absolute error in the azimuth angle estimation, especially when the mobile device is located at the angles closer to $-45°$ and $135°$. These big oscillations in the AoA estimation result in an RMSE of $24.4°$.

Fig. 9 shows the absolute azimuth error of raw AoA estimations in NLoS scenario at 4 m distance. The NLoS measurements give better result compared to the 2 m distance because we had to do AoA estimation at a smaller number of measurement points. Therefore we couldn't estimate the angles on the far left and far right part of the antenna array which cause the larger errors. The RMSE in this case is $16.81°$.

This experiment shows how AoA estimation is very sensitive and can give huge errors in indoor environments, especially in the presence of other wireless devices and multipath reflections. These results clearly indicate that raw AoA measurements can only give us a general idea of the direction of the signal. A possible way of improving the results could be to employ some filtering algorithm, such as an Extended Kalman Filter. Also, the results show that the measurements are severely corrupted, almost random, when the mobile device is almost parallel to the Antenna array 1 on both sides (less than $-20°$, more than $110°$). This is due to the linear position of the antennas in the antenna array. In LoS conditions, we take more measurement points near parallel to the antenna array compared to the NLoS, which causes a larger RMSE. When we calculate the RMSE in the LoS at the same measurement points as in the NLoS experiment,

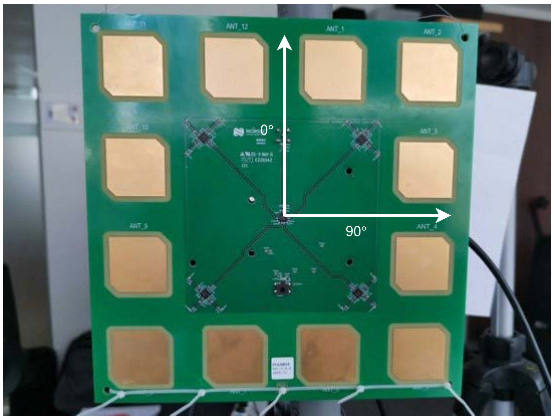


FIGURE 10. Antenna array provided by Nordic Semiconductor.

FIGURE 11. Nordic Semiconductor angle of arrival estimation test setup.

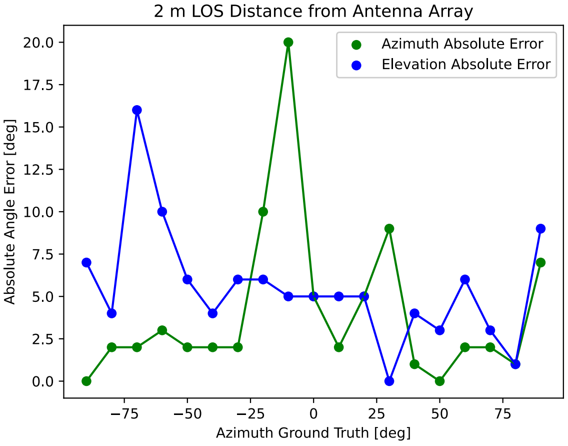


FIGURE 12. AoA estimation absolute azimuth and elevation error at 2 m distance between the mobile device and antenna array in LoS, using Nordic Semiconductor kit.

we get the expected result of better performance in LoS condition. The experiment in the Section V-B shows that we can avoid the issue of large errors near parallel to the linear antenna array by using the antenna array with the multiple antennas positioned in a plane.

B. NORDIC SEMICONDUCTOR AoA

Nordic Semiconductor offers multiple SoC development boards with enabled Bluetooth direction finding. One of them is the nRF52833-DK board which has low-power multiprotocol SoC with a wide operating temperature range. In cooperation with Nordic Semiconductor, we received the AoA development kit with two nRF52833-DK boards and antenna array for testing its AoA estimation capabilities. The antenna array has 12 patch antennas located on a square shape PCB in a plane configuration capable of estimating both azimuth and elevation angle (Fig. 10). Necessary firmware and direction viewer software was also provided by Nordic. Unlike the Texas Instruments software, Nordic's direction viewer software has the ability of showing real-time filtered data which significantly improves the result. Unfortunately, there is no explicit information on which filtering algorithm the software is using. It is also possible to obtain unfiltered angle estimations, but in order to highlight the importance of filtering the raw measurements in this experiment we collect filtered measurements.

We perform AoA estimation in the same realistic indoor scenario and configuration as in Section V-A. The testing site allows AoA estimation at 2 m LoS and 4 m NLoS distance, as shown in Fig. 5(a). We position the antenna array 2.1 m above the floor in the living room of the two-bedroom apartment (Fig. 11). The mobile device is located on the floor attached with the fishing wire to the center of the reference circle that contains the ground truth angles. Similar to the experiment with Texas Instruments' direction finding kit, we do the AoA estimations in the presence of WiFi and other wireless devices.

The antenna array with 12 antennas in a plane configuration can estimate azimuth angle in a 0° to 360° range and elevation range is from 0° to 90°. However, in this experiment, we are doing the estimation with azimuth ground truth from −90° to 90°. Elevation angle ground truth remains constant if the distance between mobile device and antenna array doesn't change. We obtain the azimuth and elevation angle at each measurement point by taking the filtered result of the angle estimation.

Fig. 12 shows the absolute error of azimuth and elevation angles at 2 m LoS distance between the mobile device and the antenna array. In this test, most of the AoA estimations of azimuth and elevation are below 10° absolute error with small number of outliers. The RMSE of azimuth and elevation is 6.17° and 6.48°, respectively.

In the case of AoA estimation at 4 m NLoS, the angle estimation results are inferior. Equivalent to the experiment in Section V-A, we couldn't estimate AoA at every test point due to the size of the apartment. We show the absolute azimuth and elevation error for 4 m NLoS distance in Fig. 13

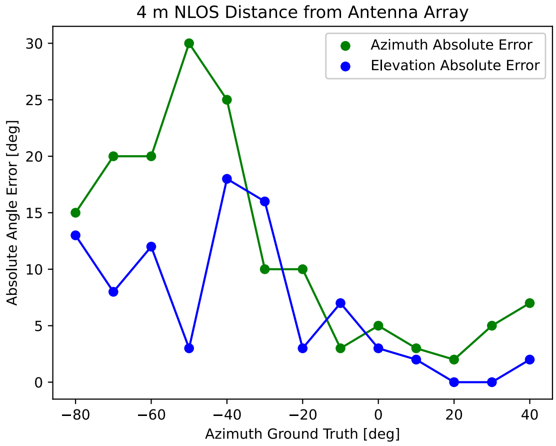


FIGURE 13. AoA estimation absolute azimuth and elevation error at 4 m distance between the mobile device and antenna array in NLOS, using Nordic Semiconductor kit.

In this experiment, we can clearly see the benefits of using filtering algorithms in AoA estimation. A filtering algorithm removes outliers and improves the overall accuracy of the estimation. As we can see from the results, the error is significantly lower when comparing filtered AoA to raw AoA measurement obtained in the experiment with Texas Instruments evaluation kit in Section V-A. Also, results show that having the antenna array with 12 antennas positioned in a plane configuration resolves the issue of outliers when the mobile device is placed near-parallel to antenna array as it can estimate angles in the 0° to 360° range. The downside is the complexity of the antenna array and its bigger dimensions. Finally, as in Section V-A for the NLoS scenario, the AoA estimation degrades because of strong multi-path reflections.

C. DECAWAVE UWB

Ultra-Wide Band (UWB) is a well-known technology used in indoor positioning systems. Its physical layer design for ToF ranging was first introduced as a part of IEEE 802.15.4 standard in 2003. The current leader on the market for providing UWB integrated circuits and modules is Decawave, with its DW1000 transceiver IC. Currently, many RTLS commercial solutions are based on the DW1000 transceiver, providing sub-meter localization accuracy [99].

In this experiment, we evaluate the accuracy and range of the UWB modules in the outdoor environment. For this purpose, we use DWM1001-DEV development boards from Decawave, which feature the DWM1001 UWB module. This development board has ranging capabilities, onboard USB connection and J-LINK which simplify firmware development. The DWM1001 module is composed of an IEEE 802.15.4-2011 UWB compliant transceiver DW1000, a Nordic Semiconductor nRF52832, a 3-axis motion detector, an UWB and BLE antennas.

In order to evaluate the ranging accuracy of mentioned Decawave UWB module we perform the outdoor ranging test in Bois de Vincennes, a forested park in Paris. For this test, we use two Decawave DWM1001-DEV development boards which run Single Sided Two Way Ranging firmware provided by Decawave. Two devices exchange messages in LoS conditions. One device is the anchor with fixed position which sends the ranging message to the mobile device and waits for the response. After the anchor receives the response back from the mobile device it calculates the distance using the time recorded for the round trip of the radio signal. We take the ranging measurements at multiple points with the anchor fixed on a tripod and the mobile device moving away, as shown in Fig. 5(b). 100 ranging measurements are taken at each measurement point, taking 100 ms for each one ranging. We use a laser distance meter to obtain the ground truth for distances smaller than 10 m between the anchor and the mobile device. For greater distances we use distance measuring tape.

Fig. 15 shows ranging measurements from 2 m to 40 m between two devices. Results show the distance measurement

FIGURE 14. Decawave DWM1001-DEV.

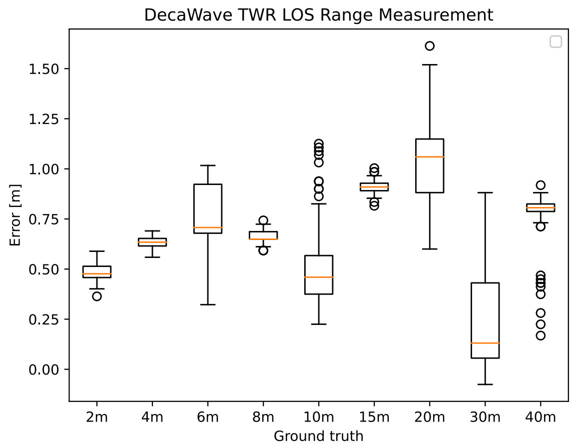


FIGURE 15. Box plot of TWR LoS distance measurement error between the two DWM1001-DEV.

error below 1 m in most cases, with some outliers being above 1 m. The range estimation in this experiment gives positive error only. This is due to the hard coded value of Tx to Rx antenna delays. In the case of the Decawave TWR firmware these values are set to give a positive range estimate error.

We find that for reliable distance estimation using the Decawave DWM1001 module the maximum range between devices in the open field is 40 m. Farther than 40 m, we did not register packet receptions, which implies that the TWR ranging cannot be performed. In order to achieve sub 0.5 m ranging accuracy we need to develop antenna delay calibration procedure for Decawave UWB modules. Antenna delay calibration is also recommended by Decawave for applications that require sub 30 cm ranging accuracy [100]. Thus, ToF estimation will include the time needed for a signal to leave from the transceiver IC to the module's antenna and vice versa.

VI. DISCUSSION

The aim of this article is to help researchers select appropriate technology and technique when developing constrained localization systems. By introducing the example use case, the localization of miniature wireless robots, we are able to present specific application requirements for low-cost and low-power solution. This allows us to focus our research and survey recent academic work on indoor localization as well as commercial products and trends that could satisfy the use case requirements. As we wanted to dive deeper into RF-based technologies and experience first-hand their performance, we conducted hands-on experiments with some of the popular AoA and ToF solutions on the market today. Experiments show the performance of these technologies, when using off the shelf products without any additional filtering algorithms. In order to summarize and discuss research results, in this section we present the main lessons learned from our study, both from academia (Section VI-A) and hands-on evaluation (Section VI-B). We also provide a discussion on complexity of the localization systems in Section VI-C

A. ACADEMIC RESEARCH

From the research conducted by various authors in light-based, sound-based and RF-based localization technologies we highlight the following.

- Light-based localization solutions usually provide centimeter level accuracy satisfying our DotBot requirement. The work done with IR lighthouse technology show promising results in terms of accuracy, battery life and cost. In order to implement this solution, the necessary hardware requirement for a mobile device is the optical receiver module. On the other hand, the anchors are off the shelf devices that don't need any additional development. However, depending on the application requirements this technology may not be suited for outdoor localization systems or those covering large areas. The main constraints of light-based technologies are limited range (5 m in case if IR lighthouse), LoS requirement and poor performance for outdoor use.
- Sound-based localization solutions are able to provide the necessary accuracy for centimeter level localization. These systems can provide bigger range than IR lighthouse. However, extending the range is power demanding and is not suited if the mobile device needs to operate for many years on batteries. Some sound-based localization systems can benefit from the ubiquity of the acoustic infrastructure in smartphones. In the case of ultrasound, we need additional hardware such as ultrasound transducers, the circuits for transmitting and receiving the ultrasonic pulse. There are some of the shelf sensors that could be considered. They are usually stand-alone devices designed to measure distance between the sensor and an obstacle. We need to develop additional hardware in order to allow these devices to measure distances between one another. Moreover, researchers need to develop solution for time synchronization between the sensors. Finally, the main constraints of these technologies are LoS requirement, higher battery consumption and unstable accuracy in different environment conditions.
- RF-based technologies are the most frequently used in indoor localization research in recent years. The work by authors cover many different RF technologies such as: Bluetooth, WiFi and UWB. Due to their poorer accuracy compared to light- and sound-based solutions, researchers use different techniques and filtering algorithms to improve the performance. The increasing market demands for indoor localization systems motivated many semiconductor companies to invest in making SoC able to provide localization capabilities. Unlike the light and sound, RF is not constrained with LoS requirement and can work in NLoS conditions. These solutions can work indoor as well as outdoor if the system uses appropriate localization technique and filtering. Selecting the appropriate RF technology can satisfy low-power and low-cost requirements. As previously mentioned the main constraint of these solutions is their limited accuracy if we use off the shelf products. Researchers need to employ different techniques and algorithms in order to improve the accuracy performance of the RF-based system.

B. HANDS-ON EVALUATION

By presenting a hands-on evaluation of commercial products for RTLS, we give reader insight into basic capabilities of Bluetooth AoA estimation and UWB ranging. The goal of these experiments is not to serve as en exhaustive comparison between different commercial solutions. Rather, we want to foster an intuition about the performance of ToF and AoA techniques, as a necessary step before selecting specific technology for RTLS. Commercial products used for these tests allowed us to quickly examine their constraints and develop our expectations.

We evaluate AoA using Texas Instruments and Nordic Semiconductor evaluation kits. From the two hands-on experiments with AoA estimation we can draw several conclusions. Results confirm that we need LoS for better AoA estimation in an indoor environment. Strong multi-path reflections and the presence of other wireless devices severely degrade the quality of the measurements. Raw AoA measurements are noisy and we need to employ some filtering algorithm in order to improve results. However, complex algorithms need higher computational power and affect energy efficiency, which is especially challenging with recourse constrained devices. Finally, there are different antenna array form factors. Number of antennas and their placement in the array has an important role on the measurements especially if we want to cover more area. This of course means more complex antenna array and bigger dimensions.

Hands-on evaluation of UWB TWR technique using popular Decawave evaluation boards showed us the range limits in outdoor LoS scenario. We measured a maximum distance of 40 m between two devices with stable communication allowing ranging between them. The ranging error give us a sense of the accuracy using off the shelf devices and default firmware. If an application requires a sub-decimeter precision, a calibration procedure needs to be developed to include antenna delays in ToF measurements.

We need to highlight that we perform AoA and ToF experiments with only one anchor and a single mobile device. A realistic deployment would have many anchors in order to cover more area and lower the positioning error, and a carefully designed triangulation or trilateration algorithm in order to estimate the location of the mobile device. Researchers have to carefully examine application requirements in order to choose the baseline technology for RTLS. These requirements dictate the necessary accuracy, update rate, battery life and cost of the system. There is no perfect technology for localization. Therefore, we underline that the most important aspect when designing RTLS is the implementation of the best suited algorithms and possible combination of different technologies, all depending on the use case of localization.

C. COMPLEXITY

In an outside/in architecture approach, a centralized system run the computationally demanding algorithms. Researchers employ schemes such as machine learning and filtering algorithms to improve the accuracy of the system. Authors report that schemes such as neural networks (NN) and regression trees (RT), used to improve AoA estimation, have a computational time of maximum 7 ms [87]. In case of RSSI-based estimations using schemes like GRNN and SVR combined with KF researchers report 4 ms computational time [90]. Most personal computers today are able to provide necessary computational power for indoor localization systems with outside/in approach.

For the distributed systems with inside/out architecture approach, we need to select the appropriate scheme carefully in order to implement the algorithm on today's low-power and low-cost SoCs. State of the art SoCs like nRF52833 provide low-power capabilities with powerful 64 MHz Arm Cortex-M4 [101]. We can easily implement techniques such as triangulation and trilateration, as well as sensor fusion on such devices. Some commercial solutions use Arm Cortex-M4 microcontrollers to implement filtering algorithms such as KF and EKF, in order to fuse data from inertial measurement units and GPS [102]. Using similar design architectures in the inside/out approach researchers can implement computationally demanding algorithms in order to improve the accuracy performance of their systems.

VII. OPEN RESEARCH CHALLENGES

Indoor localization has been a very popular research field in the last decade. While many researchers are trying to raise the bar and improve the existing localization solutions there are still many open research challenges. We identify the five main research challenges in indoor localization that are yet to be solved in order to improve existing localization solutions: lightweight filtering algorithms (Section VII-A), zero infrastructure dependency (Section VII-B), low-power operation (Section VII-C), security (Section VII-D), standardization (Section VII-E).

A. LIGHTWEIGHT FILTERING ALGORITHMS

In RF-based localization, multi-path effects and noise create big outliers in location estimation and cause low localization accuracy. This is due to the very nature of the radio signals. Transmitted radio signals can be reflected as they bounce from obstacles like walls, objects or humans. Thus, many copies of the same signal arrive at the receiver with a certain time delay. For most localization techniques, it is essential to estimate the shortest path of the signal from transmitter to receiver. This is not a trivial task and a lot of research has been conducted to solve this challenge. Typically, complex signal processing techniques and filtering algorithms are used to improve the accuracy and identify the shortest path of the signal. These techniques are usually too ''heavy'' for the resource constrained mobile devices, especially in distributed systems. Hence, there is a need for developing lightweight and efficient signal processing and filtering algorithms to mitigate multi-path effects and noise in order to obtain the shortest path of the signal. These algorithms allow mobile devices with limited processing power to obtain high accuracy, while maintaining low-power operation.

B. ZERO INFRASTRUCTURE DEPENDENCY

In most cases, indoor localization systems rely on existing infrastructure. They usually use existing Ethernet or WiFi local area networks to communicate. Also, most localization solutions provide just the localization capability and cannot handle additional data exchange between devices inside the system. Allowing devices to transfer sensor readings and actuator commands together with localization data has a huge commercial potential. When designing a zero-infrastructure system, we also need to examine the mains power constraint.

In most cases, localization systems are constrained by AC power supply requirements. Mains power is used to provide electricity to the localization infrastructure or ''anchors'' in the localization system. Overcoming networking and mains power constraints would lower installation costs and it is essential when designing a localization system in constrained environments.

C. LOW-POWER OPERATION

Depending on the application requirements, many use cases require a battery powered mobile device. In some cases, mobile device can have a rechargeable battery and the user needs to recharge it after a certain period of time. Yet, some applications require a battery-powered device with years of battery life, like our DotBot use case introduced in Section I Moreover, allowing a mobile device to be tracked without frequent changing of its battery improves user experience and reduces human labor and costs. There are many localization solutions providing years of battery life on the tag i.e. mobile device. However, battery-powered localization infrastructure with years of battery life is rarely examined. Some sound-based solutions provide battery powered infrastructure, but the battery needs to be recharged at least once every month. There are some commercially available industrial WSN, offering more than 10 years of battery life and these technologies should be considered when designing ultra low-power localization systems [103], [104]. Designing a localization system with multiple years of battery life for both mobile devices and anchors would open many different applications and presents a big commercial opportunity.

D. SECURITY

The security of localization systems and data privacy presents a significant open challenge for most applications. In industrial applications, the security issues in the localization system could cause irreparable damage to the production process or safety issues endangering people at their work site. In other applications like contact tracing in the health emergency crisis like a COVID-19 pandemic, users are not easily convinced to provide the permission for proximity detection, due to the possible privacy issues. Additionally, the limited computational power on some recourse and energy constrained devices deployed in localization systems cannot handle complex security approaches. Therefore, there is a need for developing energy efficient and computationally undemanding security system.

E. STANDARDIZATION

Unlike the Global Positioning System (GPS) which is adopted as a global standard for outdoor localization and navigation, indoor localization doesn't have its main single technology. This means that no matter how well we design our localization system once we leave the area of the deployment it is most likely that our mobile device won't work with other localization systems on different deployment sites. This is a big disadvantage and presents the opportunity for creating a universal standard which will be adopted by different devices across different applications.

VIII. CONCLUSION

This article presents a detailed survey on the recent academic research on indoor localization. We give detailed description of the work presented in the papers and provide a classification according to five different criteria: Line-of Sight (LoS) requirement, accuracy, update rate, battery life, cost. We introduce different technologies and techniques used for the development of the low-cost and low-power localization systems in the recent years, both in academia and in commercial solutions. We present the main constraints when designing a localization system through the use case of localization of miniature DotBot robots. We also present a series of hands-on experiments that we perform with RF-based commercial products used in indoor localization systems. We conduct experiments with commercial products based on Bluetooth AoA and UWB TWR. Hands-on evaluations provide first-hand insights to various constraints these technologies have. Obtained results allow future researchers in the indoor localization field to develop an intuition for accuracy in angle estimations and ranging of mentioned commercial products. Finally, we identify five main open research challenges: lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, standardization. We believe that overcoming these challenges is crucial in order to make indoor localization ubiquitous and enabled on all devices in the world of IoT.

ACKNOWLEDGMENT

The authors would like to thank Nordic Semiconductor for making their reference antenna array available. They would also like to thank Razanne Abu-Aisheh and Mališa Vučinić for proofreading the article.

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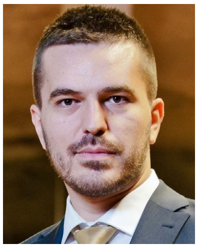

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