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Technologies and Solutions for Location-Based Services in Smart Cities: Past, Present, and Future

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ABSTRACT Location-based services (LBS) in smart cities have drastically altered the way cities operate, giving a new dimension to the life of citizens. LBS rely on location of a device, where proximity estimation remains at its core. The applications of LBS range from social networking and marketing to vehicle-to-everything communications. In many of these applications, there is an increasing need and trend to learn the physical distance between nearby devices. This paper elaborates upon the current needs of proximity estimation in LBS and compares them against the available Localization and Proximity (LP) finding technologies (LP technologies in short). These technologies are compared for their accuracies and performance based on various different parameters, including latency, energy consumption, security, complexity, and throughput. Hereafter, a classification of these technologies, based on various different smart city applications, is presented. Finally, we discuss some emerging LP technologies that enable proximity estimation in LBS and present some future research areas.

INDEX TERMS Smart cities, location-based services, localization, proximity.

I. INTRODUCTION

The evolution of Information and Communication Technology (ICT) and the advent of Internet-of-Things (IoT) has altered the way devices interact with each other. As a result, Location-Based Services (LBS) have recently emerged as an active area of research. The applications of LBS include, but are not limited to, smart cities, social networking, proximity gaming, marketing, multimedia content distribution, cellular traffic offloading, animal housing and management, healthcare, surveillance, Vehicle-to-everything (V2X) communication, and public safety.

Based on proximity, LBS can be divided into three categories. The first category includes applications that require the knowledge of location of a device, *e.g.,* locating nearest businesses or services such as ATMs or restaurants. The second category includes applications where the existence of proximity of a device meets the application's requirement, *e.g.,* local mobile advertisements to nearby devices. The third category comprises of applications wherein, along with proximity, the knowledge of exact distance between nearby devices is important for their operation, *e.g.,* for security reasons, two devices decide to connect only when they are at a fixed distance from each other.

In the literature, various technologies and techniques exist to acquire the location or proximity of devices for both indoor and outdoor scenarios. These technologies and techniques, to some extent, meet the needs of aforementioned first two categories of LBS. However, there is an increasing need and trend of finding accurate distance between two nearby devices. Concerning this, current Localization and Proximity (LP) finding technologies (LP technologies in short) do not fully meet the proximity requirement of LBS. Consequently, finding accurate distance between nearby devices remains an open research arena [1].

There exist some surveys in literature [2]–[4] that focus on specific aspects of localization in indoor or outdoor environments. However, this article summarizes many individual works to give a complete and concise picture of the status of

localization and proximity technologies in the past, present and future. Concerning this, the article first summarizes the existing technologies and techniques to find the location or proximity of devices, location accuracy of these technologies, and a brief evaluation of technologies/techniques based on their complexity, latency, throughput, energy consumption, security, and privacy. Based on this summary, we present a gap in literature to estimate the distance between two nearby devices with higher accuracy and low latency. In addition, we motivate to address security issues of these technologies without which the LBS will be subject to various vulnerabilities and attacks.

The rest of the article is organized as follows. Section II presents the potential applications of finding accurate distance between two nearby devices. Section III demonstrates the available technologies and techniques to find the location or proximity of devices. Section IV presents an evaluation of the available technologies and techniques based on certain parameters followed by a discussion in Section V. Finally, we conclude in Section VI.

II. POTENTIAL APPLICATIONS

There are many applications in LBS that require proximity information of nearby devices. Local advertisement to nearby users is one such application, which is based on proximity of the users to certain places, such as supermarket, cinema, or coffee shop. Whenever a user is in the proximity of an advertiser, it starts receiving advertisements, provided that discovery mode of the user is enabled. However, for such scenarios, the knowledge of exact distance between the advertiser and the user is not important. Similar is the case for applications like social networking, multimedia content distribution, and cellular traffic offloading. In all these applications, the existence of proximity is enough to perform their respective tasks.

There are many scenarios wherein it becomes imperative for proximity devices to learn the exact distance between them. For instance, a social game wherein a player has to maintain a certain physical distance from other players while performing certain tasks or a game wherein some features are activated only when a player is within a certain physical distance from its counter player. Besides this, the other application includes parental control on the children. A Short Message Service (SMS) can be sent to the parents informing them about the distance their child is far from them. The SMS can be turned into an alarm if the distance between parents and the child becomes significantly large.

Another example is a smart transportation system wherein the proximity information among sensors in vehicles enables them to travel with a shorter distance between them. The minimum allowed distance between vehicles could be potentially reduced to half a meter or lesser while traveling and also while standing on the road at red traffic signal. This substantially increases the road capacity, accommodating more vehicles in a shorter distance. In addition, estimating accurate distance between nearby devices has its applications in animal housing and management, healthcare, surveillance, V2X communication, and public safety.

One possibility to find the distance between two nearby devices is to use their location coordinates. The localization and positioning technologies available in literature can be utilized for this purpose. The second possibility is to directly estimate the proximity of two devices without knowing their exact location coordinates. The techniques based on Received Signal Strength Indication (RSSI) or Time of Flight (ToF), explained in Section III, can be exploited for this purpose. All these LP technologies and techniques are summarized in the next section.

III. AVAILABLE TECHNOLOGIES AND TECHNIQUES FOR LOCALIZATION AND PROXIMITY IN LBS

In this section, we briefly describe LP technologies and techniques that can be used to find the proximity of different devices in LBS. A summary of available LP technologies and techniques can be found in Table 2.

A. LP TECHNIQUES

1) RECEIVED SIGNAL STRENGTH INDICATION (RSSI)

Received Signal Strength Indication (RSSI) based localization measures the strength of the signal a device receives from a transmitter. By applying a propagation model between transmitter and receiver, the location of the receiver can be obtained with respect to the transmitter in terms of its distance. However, the accuracy of RSSI-based localization is entirely dependent on the environment and potentially fluctuates with the variations in the environment. For such reason, RSSI is generally combined with either trilateration or fingerprinting to find the location.

Trilateration is a geometric technique, which is used to observe the location of a receiver by measuring the strength of the signal it is receiving from different transmitters placed in known locations. On the other hand, *fingerprinting* establishes a database of signal strengths a receiver receives at different known locations from different transmitters. The so-called database is built in an offline phase, where signal strengths from different transmitters are saved against the known location of the receiver. Thereafter, in the online phase, this database is checked for signal strengths a receiver is getting from different transmitters to obtain the location. The accuracy depends upon the number of offline entries in the database. Thus, in general, for a given area, the bigger is the database size, the higher is the accuracy.

2) ANGLE OF ARRIVAL (AoA)

With the introduction of Multiple-Input and Multiple-Output (MIMO) technology, it is possible to estimate the distance of a receiver from transmitter by applying triangulation techniques on the Angle of Arrival (AoA) of a received signal at antennas separated by a particular distance. To calculate the AoA, a Time Difference of Arrival (TDoA) is measured by different elements of the antenna array, which is done by estimating the phase shift of the received signal in correspondence of the antenna elements.

3) TIME OF FLIGHT (ToF)

The Time of Flight (ToF) (*a.k.a.* Time of Arrival (ToA)) is another technique to obtain the distance between two devices. The timestamps provided by the wireless interface of the device are used to observe the ToF. This ToF is then multiplied by the speed of RF waves (same as light [5]) to find the distance between the transmitting and the receiving devices. The accuracy of ToF depends on the granularity of time synchronization between the transmitter and the receiver, which is a challenge for shorter distances. For instance, a distance of 2m between two devices requires a time granularity of 6.6nanoseconds [5]. Besides this, ToF can be combined with trilateration to locate the position of a device. However, in this case, three different receivers, placed at known locations, are needed to observe the ToF.

4) TIME DIFFERENCE OF ARRIVAL (TDoA)

TDoA is a variant of ToA, which requires, unlike ToA, the simultaneous transmission of two signals from with different frequencies. The signals reach the receiver at different times. The time difference is then converted into the distance. Trilateration can be exploited to estimate the position of the receiver, if we have three distance measurements from three different transmitters. In case of AoA, the TDoA between different antennas is estimated to calculate the distance.

5) DEAD RECKONING

Dead reckoning is a method of determining the current position of a moving object by using its previous known position. The accelerometer (motion sensor) and gyroscope (rotation sensor) of a device such as a smartphone can be used to estimate its speed and orientation (and thereby the position with respect to the previously known position).

6) MAGNETIC FINGERPRINTING

Magnetic sensors (compass chips) of a device can be employed to locate it inside a building by estimating the variations in earth's magnetic field due to the presence of iron objects in its proximity [6]. The compass chip can sense and record these variations and locally map the device.

7) VISUAL FINGERPRINTING

An image of a location can be used to find the position of an object with respect to known location of already installed markers. The pixel to millimeters (mm) transformation is used to estimate the position, in this case. However, the accuracy of this technique depends on the pitch angle of the camera and length of its view field [7]. Once the position of two smartphones is known, the distance between them can be easily estimated.

B. LP TECHNOLOGIES

1) GLOBAL NAVIGATION SATELLITE SYSTEM (GNSS)

GNSS is a system that utilizes satellites to detect the location (longitude, latitude, and altitude) of a GNSS receiver. The GNSS receiver receives time signals from the satellites positioned in line-of-sight with the receiver. Currently, three global GNSSs are available: the United States' NAVigation Satellite Time and Ranging (NAVSTAR) Global Positioning System (GPS), the European Union's Galileo, the Russian GLObal NAvigation Satellite System (GLONASS) and the Chinese navigation system (BeiDou). The accuracy of GNSS depends on the number of satellites in line-of-sight of the receiver. For instance, a GPS receiver requires a minimum of 4 satellites positioned in line-of-sight of the receiver. GNSS exploits the ToF, in combination with multi-lateration, to find the location of a user by using the Time of Transmission (ToT) and the location of the satellites fields in the received message.

2) ASSISTED-GNSS

Assisted-GNSS, formally known as A-GNSS, is proposed to improve receiver's operation in low-visibility environments, such as urban canyons, by getting assistance from wireless networks [8]. A wireless network gets data from unobstructed GNSS receiver and distributes it to all the customers. In particular, assistance from a wireless network improves Time-To-First-Fix (TTFF) and sensitivity. TTFF is the time required to acquire GPS signals and satellite data to calculate the location. Normally, a GNSS receiver downloads the orbital information of satellites at a speed of 50 bits per second only and it generally takes 30-40 seconds to get the receiver's position on the globe. On the other hand, in A-GNSS, this information is downloaded beforehand to a cache server managed by the network operator. Thereafter, the GNSS receiver, using cellular network, can download this information from the cache server at higher data rates.

3) CELLULAR NETWORK-BASED POSITIONING

Cellular networks, such as Global System for Mobile (GSM)/ Universal Mobile Telecommunications System (UMTS)/ Long Term Evolution (LTE), can also be utilized to find the location of a device in LBS. The techniques to estimate the location of a mobile device in a cellular network are mainly divided into two categories: Network-based and terminal-based positioning. The difference between these two lies in the place where the measurements are performed and processed. The most common position estimation techniques in a cellular network are based on: cell ID, AoA, ToA, TDoA and Enhanced Observed Time Difference (E-OTD). In E-OTD, the mobile devices and the base station (BS) are time synchronized with each other. The mobile device compares the relative time difference of the messages, broadcast from the BS, to estimate its position from each BS it is getting the messages. Each technique has its own range and accuracy.

4) WiFi-BASED POSITIONING SYSTEM (WPS)

WiFi-based Positioning System (WPS) is mainly used to locate a WiFi user inside a building. Based on this location, the distance between two WiFi-enabled devices can be obtained. The most common technique used for positioning

in WPS is RSSI and fingerprinting. However, some works in literature propose AoA and ToF as well for WPS. AoA can be used in situations wherein the access points are equipped with an array of antennas, such as MIMO. The choice of the technique depends upon the accuracy level required. The average accuracy of different techniques in WPS is presented in Table 2.

5) BLUETOOTH-BASED SYSTEM

In literature, Bluetooth is generally employed to observe the proximity of two Bluetooth-enabled devices instead of their location. However, more recently, Bluetooth-based indoor mapping has also been implemented by many vendors, such as iBeacons from Apple. More precisely, Bluetooth Low Energy (LE) is generally utilized in proximity-based applications. For most of the implementations in literature, RSSI is exploited to realize the proximity.

6) INERTIAL NAVIGATION SYSTEM (INS)

Inertial navigation system (INS) is about exploiting the dead reckoning to find the location of a device with respect to the other. For this purpose, the gyroscope and accelerometer of the device are used, which are commonly available sensors in smartphones nowadays.

7) ACOUSTIC MEASUREMENTS

Sound waves can be exploited to obtain the distance between two devices by clocking the time delay (*i.e.,* ToF) of emitted sound waves from one device. The master device generates a chirp, which is reflected back by the receiver. The time delay in this reflection is estimated, which is employed to calculate the distance between them. An application, named acoustic ruler, in Apple store exists [9] that can measure the distance between two iOS devices with an accuracy as low as 1cm. More recently, due to higher accuracy of acoustic measurements, there is an increasing trend of using inaudible sound signals to estimate the distance between nearby devices. This technology is presented in emerging technologies in Section V.

8) MAGNETIC POSITIONING

Magnetic positioning utilizes earth's magnetic field to obtain the location of an object with respect to iron objects in the building. Compass chip of a device is employed for this purpose. The mapping of two devices can be exploited to find the distance between them.

9) FM TRANSCEIVERS

FM transceiver is also proposed in literature to find the distance between two FM-enabled devices. Time of Arrival (ToA) is exploited in this scenario but instead of measuring time delay, phase delay is measured using Phase Locked Loop (PLL) of FM transceivers. The limitation of this technology is the availability of FM transmitters in smartphones. A variety of Bluetooth-enabled FM transmitters are available in the market that can be coupled with smartphones using available FM-transmitter applications for Android and iOS.

10) ULTRA WIDE BAND (UWB)

Utilizing Ultra Wide Band (UWB) to estimate the proximity of two devices is recently proposed in literature. This technology, if supported by the device, can also be used to observe the short-range distance between two devices. The techniques used in WiFi, such as RSSI and ToF, can also be used with UWB to find the proximity. The benefit of such a system is its resistance against noise due to the intrinsic nature of wide band communications.

11) CAMERA-BASED POSITIONING

Some researchers propose visual features to find the position of a camera embedded device, such as a smartphone, within the range of the camera. Pixel to mm transformation is exploited for this purpose. The accuracy of such a system is dependent on the length of the field of view and pitch angle. For a length of field of 150cm, typically an error of 12.3cm is observed [7].

Another method is to use a database of snapshots of a venue to estimate the location of a device. While moving through the location, the smartphone can take snapshots and interpolate it with the database to estimate its location.

TABLE 1. Overview of evaluation parameters of position and proximity finding technologies.

Evaluation Parameters	Description	Instantiation and Symbols
Technology Type	Type of technology to find location/position or proximity	Localization or positioning (), Proximity ()
Working Environment	Working environment of the technology	Outdoor (Out), Indoor (In)
Self Assisted	Can distance between two devices be calculated without any assistance from third party?	Yes (✓), No (✗)
Overall Complexity	Complexity of the technology to estimate the distance between devices	High (H), Low (L), Medium (M), Depends (D)
Latency	Time to find the distance between devices	High (H), Low (L), Medium (M), Depends (D)
Throughput	Throughput of data exchange between all entities involved	High (H), Low (L), Medium (M), Depends (D)
Energy Consumption	Energy consumption of technology	High (H), Low (L), Medium (M), Depends (D)
User Privacy	Technology preserves the user's privacy or not	Yes (✓), No (✗)
Security	Built-in security in technology	Yes (✓), No (✗), Depends (D)

IV. CLASSIFICATION OF DIFFERENT LOCALIZATION TECHNIQUES

In this section, we classify the aforementioned technologies based on various performance parameters or features. Such evaluation parameters are briefly described in Table 1 along with corresponding notations and symbols. We use these symbols in Table 2 to describe each technology. We consider nine distinct parameters that are relevant to proximity-based applications. These parameters are briefly described as follows.

TABLE 2. A summary of different technologies and techniques to find the distance between two nearby devices.

Available Technologies	Technology Type	Working Environment	Underlying Technique	Error and Accuracy: Accuracy (in meters)	Error and Accuracy: Confidence Level	Self-Assisted	Overall Complexity	Latency	Throughput	Energy Consumption	User Privacy	Security
Global Navigation Satellite System (GNSS)		Out	ToF	9.46 [10]	95%	✗	H	H	L	H	✓	✗
				5.39 [10]	68%							
Assisted-GNSS (A-GNSS)		Out	ToF	14.8 [10]	95%	✗	H	H	M	H	✗	✗
				8.19 [10]	68%							
Inertial Navigation System (INS)		Both	Dead reckoning	0.213[1][11]	95%	✗	L	M	M	L	✓	✗
				0.37[1][11]	67%							
WiFi-based Positioning System (WPS)		In	RSSI	4.96 [12]	75%	✗	M	M	H	M	✓	✓
				2.94 [12]	50%							
			ToF	4 [13]	80%							
			AoA	3 [14]	90%							
Cellular Network-based Positioning		In	cell ID	10-10000[2][15]	-	✗	M	L	M	M	✓	✓
			ToF, TDoA	125-200 [15]	-							
			E-OTD	50-150 [15]	-							
Bluetooth		In	RSSI	1.8 [16]	95%	✓	L	L	H	L	✓	✓
Acoustic Measurements		In	ToF	0.01 [9]	-	✓	L	L	-	L	✓	✗
Magnetic Positioning		In	Magnetic field variation	1.5 [6]	90%	✗	L	D[3]	D[3]	D[3]	✓	✗
FM Transceivers		In	ToF and RSSI	0.1-0.5 [1]	-	✓	L	L	L	L	✓	✗
Ultra-WideBand (UWB)		In	RSSI and ToF	0.05-0.1 [17]	-	✓	L	M	L	L	✓	✗
Camera-based Positioning		In	Pixels to mm conversion	Depends[4][7]	-	✓	L	L	L	L	✓	✗

[1] The accuracy of dead reckoning decreases over time.
[2] Depends on the type of the cell, *e.g.,* femto cell, pico cell, micro cell, and macro cell.
[3] It depends on the network connection between the device and the database.
[4] Accuracy depends on the pitch angle of camera and length of the field.

A. TECHNOLOGY TYPE

This feature reveals the type of technology in terms of localization or proximity. Localization indicates the position of a device in terms of device's coordinates within an environment. For instance, GNSS is a localization technology that provides longitude and latitude of a device within a global outdoor environment. On the other hand, proximity describes the sense of vicinity of two devices, *e.g.,* whether they are near to each other or not.

B. WORKING ENVIRONMENT

This feature shares the working environment of the technology, which can be outdoor or indoor.

C. SELF-ASSISTED

With reference to infrastructure support, LP technologies can be divided into two categories. In one type, distance can be estimated by exploiting devices only. On the other hand, technologies in the second category require support from third party infrastructure.

D. OVERALL COMPLEXITY

This parameter describes the overall complexity of an LP technology. The complexity depends upon the number of entities involved in the estimation of localization or proximity (*e.g.,* mobile devices, access point, and satellites), dependency of an LP technology to third party infrastructure, and the nature of the system, *e.g.,* centralized or distributed.

E. LATENCY

This parameter describes the time the devices require to calculate their location or proximity and subsequently the distance between them.

F. THROUGHPUT

This parameter is a representation of the speed of the network between the entities involved in LP technologies.

G. ENERGY CONSUMPTION

As the name suggests, this parameter demonstrates the overall energy consumption of an LP technology. The energy consumption depends on the overall complexity of the technology, its computational load on the device, and the communication interface it uses to communicate with the central infrastructure or other devices.

H. USER PRIVACY

The knowledge of user's location may reveal the privacy of the user. For instance, if the GNSS of a device is always switched-on for LBS, it can be easily tracked for 24|7 activities.

I. SECURITY

This feature describes if an LP technology supports built-in security or not. This means that whether the communication between devices in an LP technology is secured by some security protocol or not. For instance, WPS supports

WiFi Protected Access (WPA) as an intrinsic security feature of WiFi, while GNSS does not support any security feature.

Table 2 provides a summary of the evaluation of different LP technologies based on aforementioned parameters. Along with these parameters, Table 2 further elaborates on techniques that each technology employs for its respective localization or proximity purposes and the error and accuracy range of each technology.

It is evident from Table 2 that the outdoor localization technologies are generally less accurate in distance estimation as compared to the indoor LP technologies. In addition, proximity-based technologies are generally more accurate. Moreover, outdoor technologies are generally more complex, with high latency, low throughput, and high energy consumption. On the other hand, indoor LP technologies are generally more energy efficient, less complex, with low latency and acceptable throughput. Similarly, in terms of privacy, the indoor localization and proximity technologies are good in preserving privacy, provided that there is no central authority that is storing the location of a device. From a security point of view, only WPS and Bluetooth have built-in security such as WPA in WiFi and pairing in Bluetooth.

TABLE 3. Overview of assumptions and issues with different positioning and proximity technologies.

Available Technologies	Assumptions	Issues
GNSS	GNSS coordinates are known to both devices	Time synchronization
A-GNSS	GNSS coordinates are known to both devices	Time synchronization
INS	The start distance must be known to both devices	The update interval changes the accuracy
WPS	WPS coordinates must be known to estimate the distance	RSSI values are changed by the environment and in ToF, synchronization is an issue
Bluetooth	A database of pre-known RSSI values is needed	Dependent on environment
Acoustic Measurements	Both devices must have the same application installed	Speed of sound varies with room temperature
Magnetic Positioning	The magnetic fingerprints at different locations must be previously saved in a database	Moving metal objects can change the magnetic fingerprints
FM Transceivers	Both devices must be equipped with FM transmitters	Phase synchronization
UWB	Both devices must be equipped with UWB sensors	Time synchronization
Camera-based Positioning	Pitch angle and focal length of the camera must be known	Error depends on the length of view field of the camera

Furthermore, Table 3 discusses the key issues and assumptions within each LP technology. For ToF based technologies, time synchronization is an issue. On the other hand, RSSI based technologies do not provide good accuracy due to variations in RSSI values with the environment.

V. DISCUSSION

A timeline of LP technologies is presented in Figure 1. The graph demonstrates an increasing trend of research in indoor LP technologies, more precisely, the proximity. However, more work is to be conducted to estimate the accurate distance between nearby devices. For some applications, the current technologies meet the needs. However, there are numerous scenarios wherein the current LP technologies do not meet the corresponding accuracy requirement(s), as shared earlier in Section II. For example, V2X communication requires accurate distance estimation between vehicles with ultra low latency and high security.

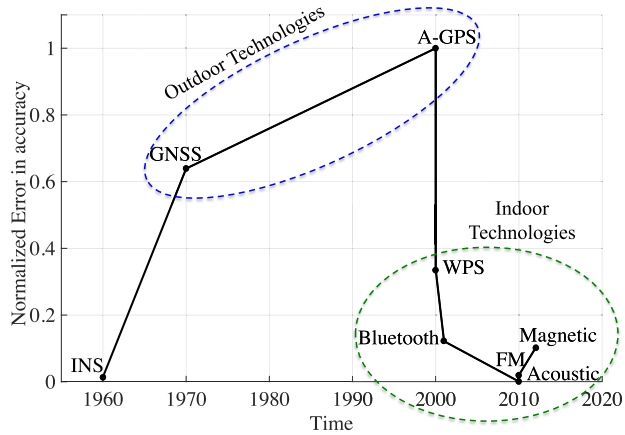

FIGURE 1. Timeline of localization and proximity technologies along with normalized error in accuracy range of each technology: Outdoor localization techniques provide larger errors as compared to their indoor counterparts.

Apart from numerous applications, learning accurate distance between nearby devices has significant potential to save energy on the wireless devices. For example in Device-to-Device (D2D) communication, if two devices know the exact distance between them, the transmit power of the signal can be substantially reduced to reach the intended device only. This not only saves energy on the devices but also provides built-in security as the signal travels smaller coverage area and reaches only the target device, which is at a certain distance from transmitter. The malicious device, lying outside the radius of that particular distance will not receive enough signal power to hear the information.

A. CLASSIFICATION OF POTENTIAL APPLICATIONS

The choice about which technology and technique to use to estimate inter-device distance depends upon the requirements of the application. For instance, LBS applications wherein a user would like to know the location and distance of his/her favorite restaurant in his/her proximity or the current location of his/her friend residing in the same city, do not require centimeter-level accuracy. For such applications, GNSS sufficiently satisfies the accuracy requirement and hence, it can be exploited. Similarly, locating a friend in a big shopping mall can be done by using any indoor positioning technology such

as WPS, Bluetooth-based positioning, magnetic positioning, and/or camera based positioning.

The applications like mobile advertisements and proximity-based social networking can exploit proximity finding technologies such as Bluetooth, acoustic signals, and FM transceivers. Although, GNSS can also be exploited, however, the device has to keep GNSS receiver always on, which is less energy efficient, less privacy-preserving, and less secure.

In applications like cross-device interactions, V2V communication, and social gaming, which require the knowledge of exact distance between devices, technologies like Bluetooth, acoustic signals, FM transceivers, and UWB can be exploited. Furthermore, a combination of such technologies can be exploited to increase the accuracy.

B. EMERGING TECHNOLOGIES

Most of the recent works in literature focus on proximity of devices instead of finding the accurate distance between them. Concerning this, some of the emerging technologies for indoor localization, proximity, and distance estimation are described as follows.

1) RFID-BASED POSITIONING AND TRACKING

Radio Frequency IDentification (RFID)-based positioning has been in research for almost a decade now [18]. More recently, there is an increasing trend of using this technology in motion tracking, that requires an accuracy in the range of centimeters. For example, enabling a virtual touch screen in the air by tracing the trajectory of an RFID on a user's finger. Some researchers propose it as a core technology in locating IoT devices. This technology generally requires multiple RFID readers and external devices, such as depth sensors and InfraRed (IR) sensors for localizing and tracking an object.

2) CSI-BASED POSITIONING

More recently, Channel State Information (CSI)-based fingerprinting is proposed for indoor localization of devices [19]. Unlike RSSI, which is temporally unstable due to multipath effects and reflections in an indoor environment, CSI is more fine-grained to mitigate the multipath effects as different subcarriers in Orthogonal Frequency Division Multiplexing (OFDM) systems travel along different fading and scattering paths.

Besides aforementioned indoor positioning technologies, there is an emerging technology, inaudible sound signals, to estimate the distance between nearby devices.

3) INAUDIBLE SOUND SIGNALS

Exploiting inaudible signals to estimate the distance between two devices is a recent technology that provides an accuracy of 1cm. *Nearby*, an application from Google, uses a combination of WiFi, Bluetooth, and inaudible sound tones to estimate the distance between nearby devices. The advantage of using inaudible sound tones is the wide availability of microphones and speakers in many modern day gadgets such as computers, smartphones, tablets, and laptops. A recent work [20] has demonstrated inaudible sound signals as a competitor to WiFi direct by turning the mobile device into a mouse in the air in order to control a smart TV in close proximity.

4) POSITIONING SUPPORT IN NB-IoT AND LTE-M

3GPP is working to standardize LTE machine type communication (LTE-M) and narrowband IoT (NB-IoT) to enable communication of everything. The positioning aspects of these technologies are not widely covered in release 13 of 3GPP. However, due to the fact that these technologies play a vital role to enable LBS in outdoor and indoor environments, the release 14 of 3GPP has a special focus on positioning in NB-IoT and LTE-M. More specifically, 3GPP has focused on Observed Time Difference Of Arrival (OTDOA), which uses UEs measure the time difference between the signals received from different base stations and apply multilateration to estimate their position.

5) ENERGY HARVESTING IN LBS

There are many scenarios in LBS when sensor nodes are equipped with batteries that deplete with the passage of time and charging or replacing batteries is not an easy solution. Energy harvesting in wireless sensor networks is an emerging technology that is used to capture and store energy from the sources present in the environment to keep the sensors working. The sources of energy harvesting include, but are not limited to, solar power, radio frequency on which the sensors operate, thermal energy, kinetic energy, wind energy and salinity gradients energy or blue energy, which is produced from the difference in salt concentration between seawater and river water. A practical example is the wireless sensor network deployed in forests by a research team at Massachusetts Institute of Technology (MIT) to predict and track forest fires. The sensors take energy from the electricity produced by the trees themselves.

C. FUTURE RESEARCH AREAS

1) HYBRID TECHNOLOGIES

Some researchers propose a combination of multiple technologies to increase the accuracy, such as Bluetooth combined with inaudible sound signals or inertial sensors. Recently, a work [21] has demonstrated the combination of Bluetooth low energy, inaudible sound tones, and inertial sensors to estimate the distance between devices and their orientations with respect to each other. However, a smarter combination needs to be explored that should meet the energy requirements of LBS with increased accuracy and latency.

2) MIMO BASED DISTANCE MEASUREMENTS

Incorporating AoA in modern day multi-antenna devices can increase the accuracy of distance measurement in proximity-based applications. Although, some works in literature propose AoA-based indoor localization in WPS, when WiFi access points are equipped with multiple antennas. However, exploiting AoA in direct Point-to-Point (P2P) distance

measurement between MIMO equipped devices using different technologies such as WiFi, Blutooth, remains an open area of research.

3) SECURITY OF LP TECHNOLOGIES

Apart from localization, proximity or distance estimation, most of the LP technologies discussed in this article are vulnerable to different security attacks. Most of the technologies do not support any built-in security feature, *e.g.,* GNSS, INS, acoustic signals, magnetic positioning, FM transceivers, UWB, and camera-based positioning. For instance, the GPS receiver of a theft car can easily be hacked to send wrong location to its owner. Similarly, in V2V communication, manipulating the location of moving vehicles or distance between them can significantly increase potential accidents on the roads. In the same way, a malicious user, knowing the working frequency of inaudible sound signals can generate the same frequency to confuse the legitimate users regarding their distance. Although there is a research community focusing on securing the communications part of LBS, an extensive research study is required in securing the localization part of LBS that must span across all localization and proximity finding technologies. However, bearing the importance of security in many LBS applications, European GNSS Agency (GSA) has recently dedicated its efforts to incorporate authentication services in the Galileo navigation systems.

VI. CONCLUSION

This article provides a summary of available localization and proximity technologies and a classification of these technologies based on various different performance parameters. Moreover, we demonstrate that these technologies are not sufficient to meet the accuracy needs of many applications in LBS. However, some emerging technologies (such as MIMO, LTE-M, and NB-IoT) exist that provide proximity information with higher accuracy but more research contributions are required to leverage a combination of emerging and current technologies to achieve higher accuracy. In addition, we remark that security is a least addressed topic in current localization technologies. However, the emerging localization technologies such as LTE-M, NB-IoT, and 5G may incorporate strict security features in their standards.

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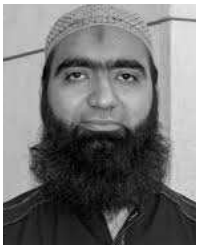

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