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Localization for transportation and urban planning in smart cities: interest, challenges, and solutions

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ABSTRACT

The concept of a smart city represents an innovative approach to urban development, aiming to enhance residents' quality of life by making cities more adaptable and efficient through the integration of advanced technologies. In recent years, the Internet of Things (IoT) has been widely applied in various smart city domains, including communication, healthcare, and transportation. However, localization has emerged as one of the key challenges in IoT implementation. Localization plays a crucial role in smart city development, as it is essential for effective urban planning, traffic management, and optimizing public transportation routes. Accurate location data enable personalized services for citizens, such as activity recommendations and real-time alerts about local events. Furthermore, by optimizing travel and improving resource management, localization contributes to urban sustainability by reducing waste and enhancing overall efficiency. This research makes several contributions. First, it examines the significance of localization in smart cities and highlights the associated challenges. Next, it explores various indoor and outdoor localization technologies, analyzing their advantages and disadvantages while providing a comparative assessment. The manuscript also classifies communication networks within smart cities, detailing their characteristics. Additionally, it discusses various machine-learning algorithms used to address localization challenges. Finally, it reviews related works in the field, providing insights into existing solutions and future research directions.

1. Introduction

Since the emergence of the notion of intelligent objects or the so-called Internet of Things (IoT) for more than 20 years [1], many research works have been conducted in the field of wireless intelligent sensor networks. Moreover, scientists have become more interested in studying the relations between these objects and the devices through which they can be effectively linked. Nowadays, the number of connected mobile devices and things in (IoT) is constantly and rapidly increasing. However, despite the availability of a large number of localization solutions in the literature, the rate of localization precision they provide remains low. Besides, the localization technologies are also highly energy-consuming and exceed the capacities of the energy resources present in certain wirelessly connected objects. In this context, localization of mobile equipment can be defined as a technique used to provide valuable data considered to analyze the activities of a given city because, for example, informed decisions can be made for the development and improvement of the resident's quality of life by studying the traveling patterns and demographic trends. Thanks to the precise knowledge about the location of mobile equipment, cities can provide smart urban services such as smart parking, demand-based waste collection, adaptive public lighting, etc. Therefore, the techniques applied to analyze these data in order to deduce the location of the objects should be optimized in many applications used in such networks. As demonstrated in [1], localization approaches can be classified into three categories: the distributed approach, the centralized approach, and the hybrid approach. An extensive study of the literature shows that optimization and learning methods are extremely efficient for data analysis in an IoT network [2].

This research contributes to the study of existing localization techniques used in the Internet of Things (IoT), providing a detailed analysis of their approaches, measuring techniques, and localization techniques. Furthermore, it includes a comprehensive comparison of various localization methods.

The first section describes the problems and interests of localization. Section 2 presents the method and related work. Section 3 presents a detailed survey of indoor and outdoor localization technologies. It also compares them by enumerating their advantages and disadvantages. Then there are depictions of the existing resolution approaches. Finally, this research presents the algorithmic solutions, adapted to deal with the localization-related problems, and illustrates their advantages and disadvantages. Finally, the paper ends by providing a description of the existing systems and proposing several research perspectives.

2. Method

2.1. Problem statement

Localization consists of determining the optimal position of an object [1] [2], a service, or a resource. The localization of mobile equipment provides valuable data to analyze the activities of a given city as it informs people about the development and improvement of the resident's quality of life. By determining the location of mobile equipment, cities can provide smart urban services such as smart parking, demand-based waste collection, adaptive public lighting, etc. Localization is characterized by three main parameters. Fig. 1 below presents the different approaches and techniques of localization in IoT.

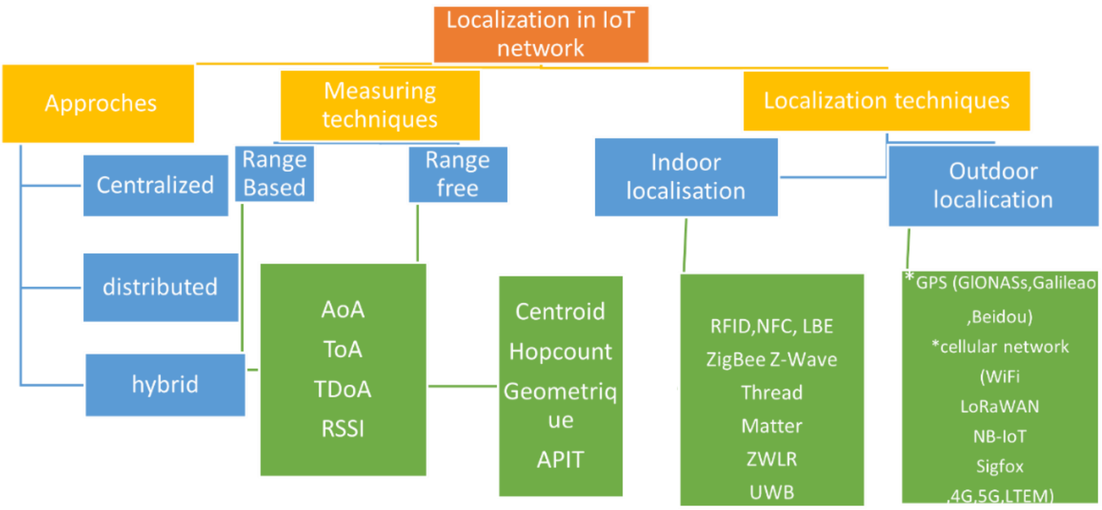

Fig. 1. Localization in IoT network

2.2 Localization methods and algorithms

Several localization methods, like trilateration, triangulation, fingerprint recognition algorithms (Fingerprinting), and probabilistic methods, were introduced in the literature. Trilateration is generally applied to measure the distance between nodes [3] and is widely employed [1] - [4] in the localization process, while triangulation (intensively used in localization [1] - [4]) measures the angle between nodes. When the angle is greater than 3, n-lateration or n-angulation are rather employed. Fingerprinting algorithms, based on the learning phase, create unique fingerprints employing wireless signals (e.g., Wi-Fi or Bluetooth) or other radio waves (e.g., LoRa) to determine the position of a device in a given space [5]. On the other hand, probabilistic methods, such as Kalman filters and particle filters, estimate the position of objects by considering measurement uncertainties and errors. In the last decades, new artificial intelligence (AI) paradigms have emerged to improve the accuracy and efficiency of localization in IoT networks, considering consumption constraints, energy consumption, precision, and cost of sensors. These new AI techniques rely on optimization applying evolutionary and meta-heuristic algorithms, machine learning and deep learning.

2.3 Problems related to localization via IoT

Localization problems leveraging IoT (Internet of Things) networks essentially provide solutions to challenges related to the accuracy, reliability, and power consumption of the localization systems. IoT devices use communication technologies, such as GSM, Wi-Fi, and Bluetooth, as well as other sensors (e.g., such as signals from the Global Navigation Satellite System (GNSS), the American Global Positioning System (GPS), the Russian system (GLONASS), the European GALILEO system and the Chinese BEIDOU system) to determine their geographic position. However, GNSSs face some problems like interference, poor network coverage in enclosed sites, physical obstacles, or measurement errors, which affect the accuracy of the location. Moreover, they cannot detect the location of mobile objects in the indoor environment. Additionally, energy consumption is a major issue that should be measured to assess the performance of IoT devices as most run-on batteries. Moreover, energy-efficient localization techniques allow extending the battery lifetime and ensure the proper functioning of the connected devices. To solve the above-stated problems, several research works, like [6-12], proposed innovative solutions, such as the employment of Machine Learning, to improve location accuracy, the optimization of localization algorithms to reduce energy consumption, and the integration of several localization technologies into localization systems. However, it may be wise to exploit the large amount of data generated by IoT networks and use it directly to offer better location service. Localization faces also several optimization problems that should be solved to find the optimal configuration and, consequently, to attain specific objectives in many fields [13] (e.g., logistics, telecommunications, marketing, computer science, etc.). Optimization is, therefore, important in the localization process to achieve the best possible results in terms of precision and energy consumption, while exploiting large quantities of data. Previous studies [14]-[15] showed that most localization algorithms were applied to enhance precision, minimize errors and optimize energy consumption. The present work demonstrates that optimization and learning methods, such as the principle of k-nearest neighbors (kNN), support vector machines (SVM), and decision trees, are efficiently applied to analyze data in an IoT network [16]. For instance, machine and deep learning in an IoT network can be used to detect complex patterns and relationships between IoT data [14]-[16] providing useful insights about the behavior of the connected devices and the employed sensors. Learning algorithms also make it possible to maximize the utilization of IoT network resources.- Additionally, learning algorithms can estimate future trends of IoT devices and their functioning to ensure sustainable maintenance of IoT networks, good energy management, and efficient resource planning.

In summary, the use of optimization and learning methods to analyze IoT localization data enables dynamic adaptation to environmental changes by providing data useful to make decisions, optimize data processing operations, and enhance the IoT network's overall performance. The literature review reveals that few research works proposed localization techniques based on the combination of optimization algorithms and learning techniques. For this reason, this study deals with the resolution of location optimization problems by applying a hybrid method, combining meta-

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heuristics and machine learning, on large quantities of data provided by IoT networks in a city. Several approaches were developed to study the optimization of localization problems. However, few studies were conducted to solve optimization problems in outdoor and indoor environments using machine learning [14].

2.4 Outdoor/Indoor localization technologies

A smart city uses the Internet of Things (IoT) to improve urban services and manage its resources as well as to transmit and analyze voluminous data in real-time. To ensure that each city service runs smoothly, smart cities must carefully choose the appropriate networks in which their IoT projects will be performed. In the following sections, the different types of communication networks used in smart cities will be stated. Both outdoor and indoor geolocations face the same challenges: making the position of equipment more visible and optimizing the activities of the objects in an IoT network. The most intensively employed technologies and their characteristics are defined below. Internal and external localization technologies are also presented.

2.4.1 Outdoor localization technologies

- **GPS**

GPSs, including the Russian Global Navigation Satellite System (GLONASS), the European Galileo system, and the Chinese Beidou system, are among the first introduced geolocation systems and the most widely used today [17][18]. Although they are effectively utilized in outdoor geolocation, they are unable to meet indoor positioning requirements. Positioning via GPS offers accuracy between 5 and 50 meters. However, it requires the highest energy consumption, compared to other technologies, such as WIFI and LoRaWAN, which are, admittedly, less precise. Added to that, GPS has other limitations like high energy consumption and indoor geolocalization.

- **The Wi-Fi network**

Nowadays, the Wi-Fi network is considered as a powerful geolocation solution [12]. It is a good alternative to GPS, particularly in urban areas, because it consumes less energy. This geolocalization system uses the known position of certain WiFi networks to determine the position of a device. It offers a precision of approximately 10 and 50m. This technology, which consumes a reduced amount of energy (3 to 5 times less than GPS), allows good precision, particularly in urban areas. It should still be noted that, unlike GPS, utilizing WiFi, the device sends the collected access points to a cloud in order to determine its position.

- **The cellular network**

The cellular network does not only connect objects to the internet via a telephone, but it is also a reliable geo-localization tool, which makes localization via cellular networks operate as that via Wi-Fi access points. Indeed, such networks employ relay antennas to transfer data from mobile phones. The localization accuracy varies depending on the number of cell towers. For example, in the city, an accuracy between 250 m and 1 km can be obtained, while, in the countryside, it ranges from 1 to 2 km.

- **The LoRaWAN network**

The LoRaWAN network proves to be a cost-effective and efficient geo-localization solution. In fact, it relies on the LoRa antennas of an already-existing public network. This technology has several advantages such as easy deployment, long range, and low energy consumption [19]. Moreover, LoRa devices are accessible and simple to integrate into a network [24] because they have a long-range (several tens of km) and require small infrastructure (a few LoRaWAN gateways). A LoRa radio link works in a sub-gigahertz radio band and its modulations are very robust and not very sensitive to interference [19]. This network utilizes radio frequencies 868 MHz, in Europe, and 915 MHz in the United States.

- **NB-IoT**

This narrow-band Internet of Things network is a low-speed network (250 Kbit/s) having a relatively high latency (1 second). NB-IoT makes the connected objects able to operate for 10 years without any interruption [20].

- **Sigfox**

SigFox is a long-range wireless communication technology (operating between 30 and 50 km, in rural areas, and at 3-10 km in urban areas) [21] having a low data rate (up to 12 bytes per message). However, it has short bandwidth and limited real-time tracking support. Emerging first in Toulouse, this technology lost momentum after the appearance of the commercial crisis and the subsequent administrative problems. Therefore, it was advantageously replaced by LoRaWAN.

- **4G**

The fourth generation (4G) network is a communication network standard that offers higher data rates than the previous generations [22]. The 4G network has significantly contributed to the rise of smartphones and bandwidth-intensive applications.

- **5G**

The 5G network is the latest innovation in mobile network technology [23]. It enables ultra-fast communication using both high frequencies and wideband [22]. The integration of AI into IoT-based 5G networks is crucial for the success of the IoT network [24]. LTE-M (Long Term Evolution for Machines), the protocol part dedicated to IoT of the new 5G standard, emerged after 5G. It ensures fast connectivity and low power consumption. It is ideally used in applications requiring frequent data transfers.

2.4.2 Indoor localization technologies

Indoor Localization technologies have become an essential part of people's daily life with the large proliferation of smart devices [25][28].

- **Radio-Frequency Identification**

Radio-frequency identification (RFID) communication network is based on the transfer of data between RFID tags and an RFID reader via radio waves. RFID labels, also called tags, are assigned to objects to uniquely identify them. RFID is often utilized in labels or badges to collect data [27]. This technology is precise in localizing objects in small areas and is simple to use [19]. However, the emitted signal is attenuated if the environmental conditions are unstable.

- **Near Field Communication**

Near Field Communication (NFC) is an ultra-short-range wireless communications technology that is primarily employed in secure, standards-based payment transactions [28] and other similar applications. When used in indoor locations, NFC exhibited reduced power consumption, excellent precision, and low cost. It has some limitations such as interference from metallic objects and electromagnetic [29]. On the one hand, due to their very short range, the two techniques (such as RFID and NFC) require very wide deployment of RFID and radio readers in large cities.

- **Bluetooth Low Energy (BLE)**

It is a low-power communication technology [28][30]. BLE standard coverage distance is around ten meters with a maximum power of over 100 meters. It appeared after Bluetooth which has a higher speed than BLE.

- **ZigBee**

Zigbee is a short-range wireless communication protocol based on the IEEE 802.15.4 standard. It is a low power consumption, low data rate, and short-range wireless network [28][31]. This topology uses a star, mesh, or cluster topology to form networks of sensors and connected devices. The Zigbee signal propagates in an indoor environment [32].

- **Z-Wave**

Like ZigBee, Z-wave is a medium/short-range wireless mesh networking technology. It is essentially applied in thermostats, door locks, home automation, lighting, smoke detectors, security, and other home appliances [33]. It transmits data at 868,42 MHz, in Europe, and at 908,42 MHz in the United States.

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Z-Wave devices are more expensive than other similar wireless technologies (e.g., Wi-Fi). On the other hand, they are quite susceptible to interference from other wireless devices employed at home, which can affect communication reliability. The importance of this technology is diminishing nowadays.

- **Thread**

Thread is a communication protocol maintained by Thread Group [34]. It solves the complexities of IoT by addressing some challenges such as interoperability, reach, security, energy, and reliability. Thread networks have no single point of failure and are self-heal. The radio technology employed by Thread is the IEEE 802.15.4 wireless protocol which has mesh communication and uses 6LoWPAN.This protocol also connects securely devices to the cloud, making it easier to control IoT systems using some devices such as mobile phones and tablets [34]. It was designed to meet the requirements of applications requiring limited power consumption, low data rate, and short communication range [35].

- **MATTER**

MATTER is a smart home network protocol that ensures increased interoperability between different devices and brands [36]. It allows devices to communicate locally, even in the absence of the internet and simplifies the manufacturing of new products while improving the user's experience.

MATTER is considered a universal approach. Standardizing the way devices communicate, makes it easier to integrate and control devices of different brands within the same network, which creates a consistent and easily manageable connected home. The radio technologies used in MATTER (formerly Project CHIP) include Thread wireless protocol and Bluetooth LE. When applied in wired technologies, MATTER considers Ethernet. The aforementioned technologies are combined to create a unified connectivity standard for smart devices in connected homes.

- **Z-Wave Long Range (ZWLR)**

ZWLR is a new method of Z-Wave connectivity. Soon available in the European market, ZWLR is considered a communication protocol having high performance and low power consumption. It also ensures increased device security [37].

- **UWB**

Ultra-wideband (UWB) is a medium-range radio communication technology standard. It offers low power consumption that is higher than that of BLE and has some advantages over WLAN since it is not affected by other RF signals [30]. The maximum communication distance is approximately ten meters [38] It is characterized by its high location accuracy (10 cm) based on the distance measurements made by radio Time of Flight. Fig. 2 below presents a comparison of the short-range communication networks (<10 m). Then, a comparison of the medium-range communication networks (10 to 100m) is shown in Fig. 3. In addition, a comparison of long-range, and low-speed networks (>100m) is presented in Fig. 4.

2.5 Comparison of Indoor/Outdoor localization technologies

In this section, the different indoor and outdoor localization technologies are compared in Table 1. It compares various localization systems based on key performance metrics, including precision, measurement type, scalability, complexity, energy consumption, cost, reactivity, benefits, and disadvantages. GNSS offers real-time localization with easy installation but suffers from slow processing and high maintenance costs, while Wi-Fi provides high scalability and infrastructure availability but faces interference issues and high initial deployment costs. Bluetooth ensures fast data transfer without the need for additional infrastructure but has limited coverage, whereas LoRa is optimized for IoT networks with long-range capabilities but low data transmission rates. FM provides strong signal coverage over large areas but experiences signal fluctuations over short distances, while UWB delivers the highest precision and interference-free performance, though it is constrained by limited coverage and performance degradation in non-line-of-sight (NLOS) conditions.

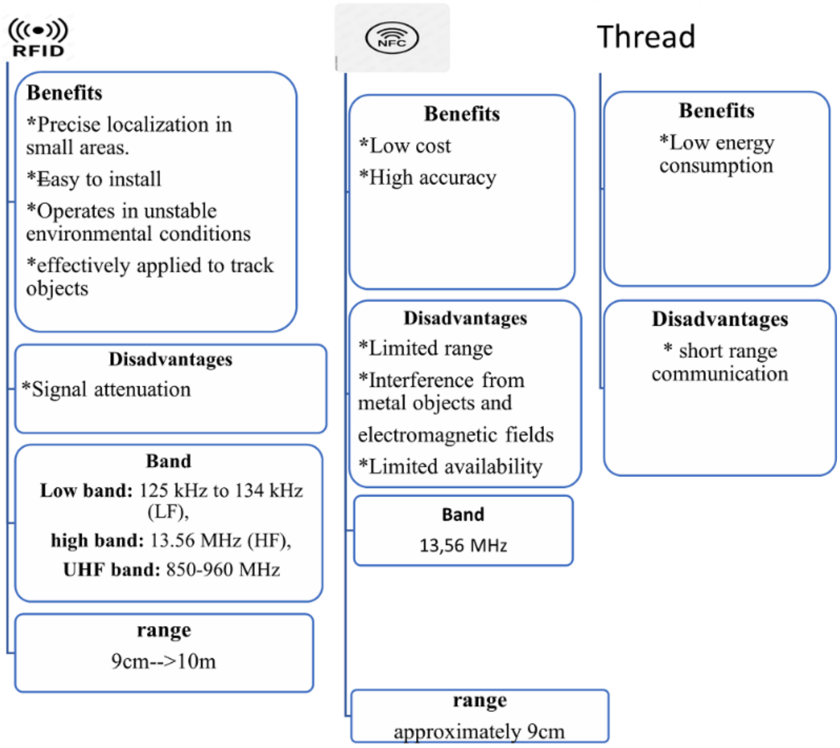

Fig. 2. Comparison of the short-range communication networks(<10 m)

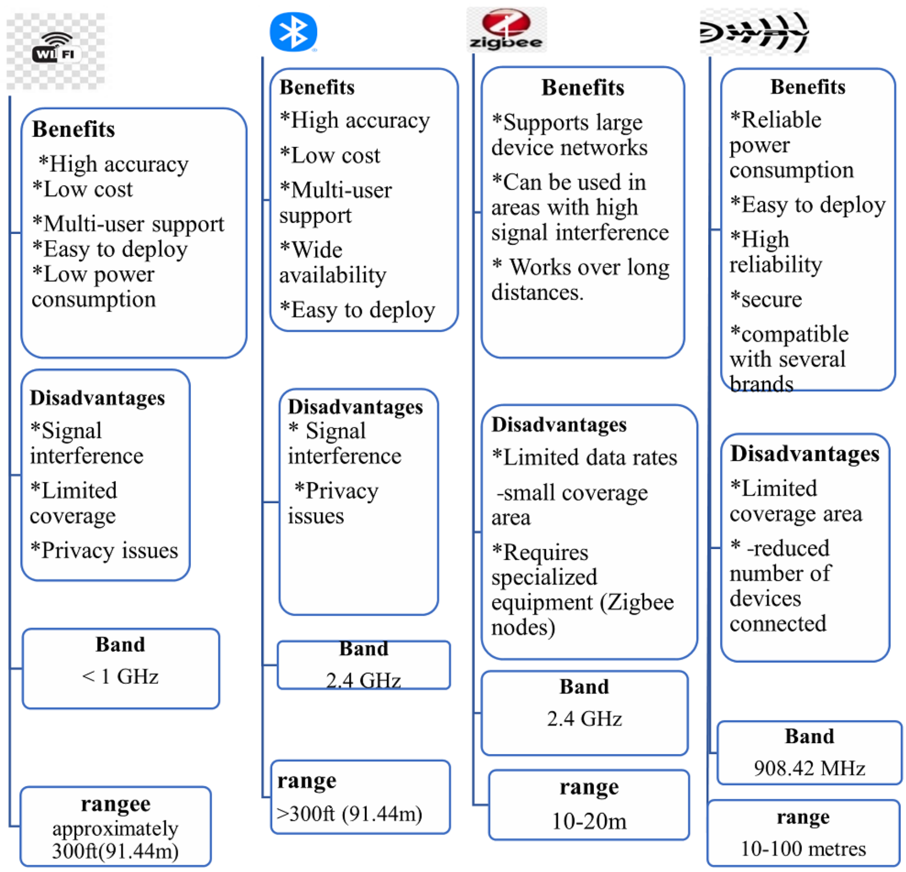

Fig. 3. Comparison of the medium-range communication networks (10 to 100 m)

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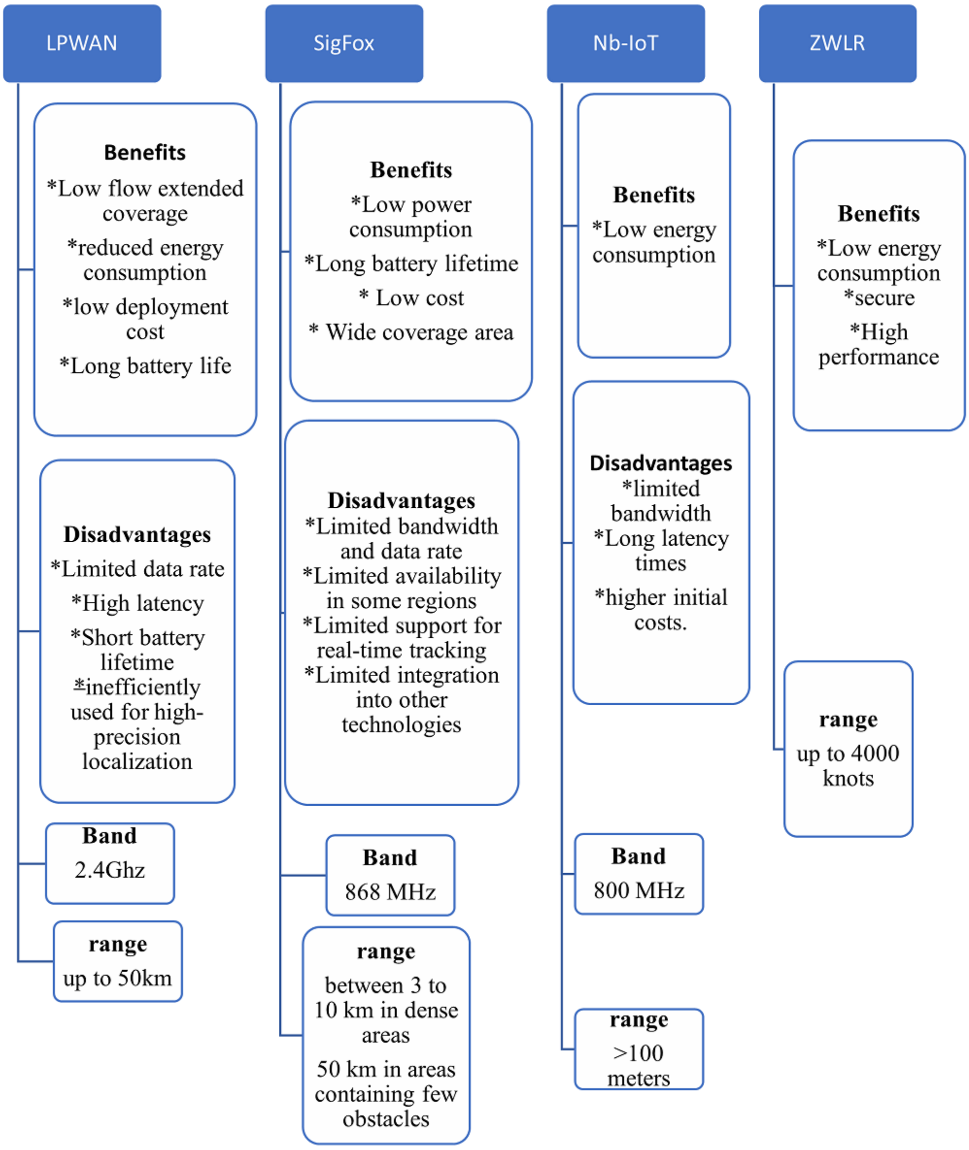

Fig. 4. Comparison of long-range, and low-speed networks (>100 m)

2.6 Localization techniques

Indoor and outdoor localization faces several challenges due to the presence of moving or stable obstacles in a given environment. Various techniques were developed to provide precise localization and locate mobile or fixed objects in outdoor and indoor environments. The existing location techniques are described below.

- **Vision-based technique**

The vision-based localization technique relies on scene analysis that recovers scene features from videos and images without considering electromagnetic signals [39]. The target device position is estimated by comparing the measurements calculated online with those extracted from the closest features. This technique is characterized by its robustness when used in environments containing high geometric distortions [40]. Moreover, its performance is not affected by the lighting variations. The vision-based technique is effectively employed in outdoor/indoor localization.

- **Dead Reckoning**

It is a tracking method applied to determine the position of people using inertial sensors such as accelerometers and gyroscopes. It can also be run on commercially available hardware like smartphones and smartwatches. PDR is primarily utilized to update the wearer's position, based on step detection, and the object location using the last position and step length in real time [41].

Table 1. Comparison of the indoor/outdoor location technologies

System	Precision	Measurement type	Scalability	Complexity	Energy consumption	Cost	Reactivity	Benefits	Disadvantages
GNNS	3 to 5m	TOA, TDOA	Low	High	High	high	Real-time	Ease to install	*Slow processing time *High maintenance cost
Wi-Fi	1 to 5m	RSSI, RTT, TOA, TDOA, AOA, AP-Id	high	Low	High	Low	Few seconds	* Infrastructure available everywhere	*Its initial deployment is expensive. *Multi-path sensitive. *Interference problem
Bluetooth	1 to 3m	AP-ID, RSSI, TOA AoA	high	Low	Low	Low / medium	Few seconds	*The speed of data transfer is high. *No need for an infrastructure	*Limited coverage RF interference of the signal
LoRa	2 to 15 m	TDOA, RSSI	Medium	Low	Low	Medium	Few seconds	*Designed for networks IoT and sensor networks. *Long battery lifetime *Long range,	*Considerable signal attenuation *Low transmission rate data (some kilobytes). *Low precision
FM	2 to 4 m	RSSI	Low	Low	Low	Low	Few seconds	* Strong signal *coverage large areas.	*Signal change occurs in short distances.
UWB	0.01 to 1m	TOA TDOA RSSI AOA	Low	Low	Low	high	real-time (real-time Reactivity	*No interference	*Performance degrades to NLOS *Limited coverage

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Dead Reckoning shows high performance when integrated into GPS/GNSS technology. It gives high accuracy in calculating the current location using data from multiple sensors including gyroscope, accelerometer, speed, etc. [17]. Its main disadvantage is essentially related to the accumulation of errors over time. This technique estimates the movements of objects based on a starting position. Any inaccuracy in the measurement of movements or environmental variables can lead to an estimation error.

- **Proximity technique**

It is a major localization method that evaluates the position of a target device relative to a predefined location or region. The proximity technique is characterized by its easy implementation, low power consumption, good accuracy, and ability to operate in environments where GPS may be limited or unavailable. On the other hand, it exhibits limited accuracy in complex or dense environments, reduced range, due to the need for physical proximity, and susceptibility to electromagnetic interference or other disturbances that can minimize location reliability.

- **Multi-lateration**

Multi-lateration techniques, such as ToF, TW-To-A (RTT), and TDoA (TDoF)[43], are applied to estimate the location of a node from reference points with known posts.

- **ToA /ToF**

It stands for Time of Arrival (ToA)/Time of Flight. It is the time interval between the transmission time of radio waves from a transmitting point and the arrival time to a receiving point. This method is utilized in GPS localization systems [42].

AOA-based techniques have a few limitations. Indeed, they utilize many antennas to measure the angles, improve the precision of the localization system, and increase the implementation cost. Besides, they suffer from multi-path and NLOS signal propagation problems [17].

- **Two-WayToA (TW-ToA)/RoundTrip ToF(RTT/RTToF)**

ToA methods require device synchronizations. In fact, TW-ToA or RTToF techniques use round-trip delay between the receiving and the sending nodes to eliminate common clock requirement issues.

- **TDoA/TDoF**

The TDoA (Time Difference of Arrival) technique consists of measuring the round-trip delay between the receiving nodes and the sending nodes to determine the position of the signal [43].

- **RSSI Propagation and Fingerprinting**

The RSS detection method is based on the indicator of power loss that the signal undergoes in the propagation medium because the signal decays in free space. It applies the Received Signal Strength Indicator (RSSI) parameter to locate an object in a medium.

- **Triangulation (AoA)**

AoA is based on the principles stated below:

1. The source emits a signal which is generally a radio signal.
2. Antennas or sensors receive the signal from different directions.
3. The receiver processes the received signals to determine the arrival angle of the signal.
4. Using the angle of arrival and other relevant information, the tracking system estimates the position of the signal source. The principle of AoA is presented in Fig.5.

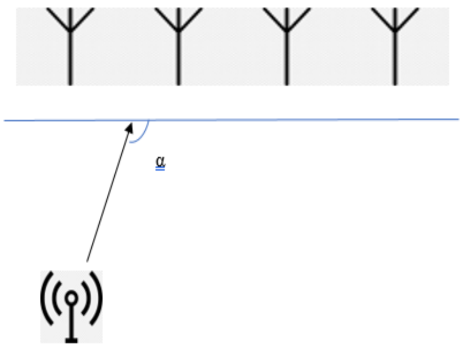

Fig. 5. Principle of AoA

- **Map-Matching**

The process of connecting the estimated position of the target mobile device with the geographic information retrieved from the digital map is known as map matching.

- **Hybrid methods**

Combining more than one approach in a hybrid method can overcome the limitations of each technique and improve its reliability. Fig. 6 below describes the possible hybrid method.

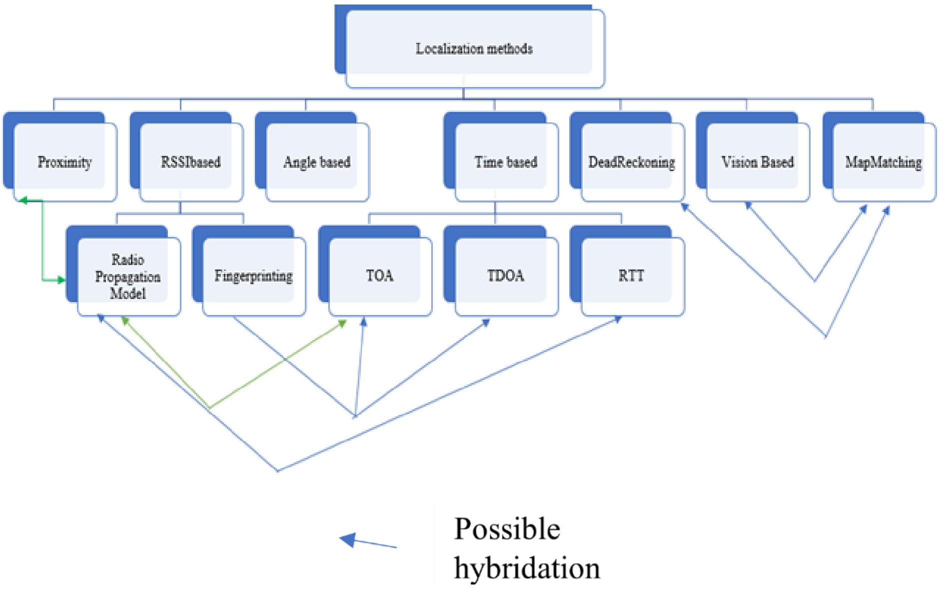

Fig. 6. Possible localization methods

3. Results and Discussion

3.1 Related Works

The approach proposed by Perkovic et al. [44] uses LoRaWAN technology and neural networks to predict the locations of mobile objects in a university building. RSSI and SNR metrics were utilized to measure the signal strength. The position was estimated according to the variation in the signal strength. The obtained results reveal that the latter achieved an accuracy of up to 98.8% and, consequently, a low error rate. However, the authors did not compare the provided findings with those given by other solutions using RSSI and SNR metrics.

The approach of Zeaiter [45] relying on AoA as a measurement technique, provided an accuracy of 5%, if the signal was strong, and 12% if the signal was weak in an indoor environment. Research demonstrated that AoA can be used to successfully locate a LoRa transmitter in indoor environments. However, the introduced approach shows that the LoRa network is not effectively employed in outdoor localization.

Yadav et al. [46] proposed a CCM-RL algorithm in which each node calculates its optimal action separately to exploit the scan rate and maintain network connectivity. The main objective of CCM-RL is to help SNs acquire their exploit optimal to trigger the nodes in each scheduling cycle, to become the lowest optimum, and maintain the standards of exposure rate and connectivity of the system. The evaluation of CCM-RL with the considered algorithms reveals its high accuracy and consistency. The obtained results show an average error rate of less than 1.5 meters, in the indoor environment, 0.5 m, and 1.5 meters in an outdoor environment. Despite their importance, these findings were provided through simulations using Matlab software.

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Kim et al. [48] introduced an approach based on LoRaWAN networks and the RSSI technique. The experimental results reveal that the approach gave an error rate of 1.6 m, in LOS, and 3.1 m in extreme NLOS conditions.

Purohit et al. [49] suggested an outdoor localization system relying on LoRa. The simulation results were obtained by applying deep learning models and traditional methods. It was also noticed that deep learning models outperformed machine learning models such as KNN, SVR, and linear regression (LR). Moreover, the approach achieved the best average localization error of 191.52726 m using 64 neurons, with a batch size equal to 512~~,~~generations, at 10, and dropout at 0.1 to avoid overfitting.

Pham and Mai [50] utilized the Wi-Fi-RSSI measurement to train an ensemble model composed of a DNN model and two other models constructed by machine learning techniques such as K-nearest neighbors (KNN) and random forest (RF) algorithm. The developed models gave better results than those provided by each model if used separately. Indeed, the average error obtained by the model introduced during the test was 1.10 m.

Li and Hu [51] introduced an algorithm extended to Kalman filter-based detection and localization. In their approach, multiple anchors were detected simultaneously. This algorithm gave an accuracy of 2%, for indoor localization, and an error of 2m for outdoor localization.

Valiente et al. [7] proposed an approach based on the Wi-Fi communication network with RSSI. The indoor localization results obtained in a space of 72*72 meters with 2.4 Ghz show an accuracy of 71.28% and an error of 1.9 m. On the other hand, outdoor localization results were provided in an environment of 200*120 meters. An error rate of 0.49 was obtained. However, these simulation results given using MATLAB should be confirmed by simulations. Table 2 summarizes the existing localization approaches introduced from 2019 to 2023.

3.2 The existing machine learning algorithms for outdoor and indoor localization

Each learning technique has some advantages and disadvantages.

- **K-Nearest Neighbors (KNN)**

The k-Nearest Neighbors (kNN) algorithm is a supervised learning algorithm [52] that is easy to implement. It is also robust to noisy data. However, it is sensitive to large volumes of data, which increases the calculation time and algorithm complexity. This algorithm requires a base of training data as it computes the distance between two points. On the other hand, k-NN can be sensitive to outliers because it relies on the proximity of neighbors to make decisions.

- **Support Vector Machines (SVM)**

Support vector machines (SVMs) are effectively utilized in large spaces and datasets [16]. Additionally, SVMs maximize the margin between classes, which promotes better solution generalization and reduces overfitting [53]. In addition, SVMs manage non-linear data [54]. According to [19] and [52] it is important to note that these algorithms can be sensitive to the choice of parameter, and they are expensive in terms of computational time when applied to large datasets.

- **Decision trees (DT)**

A decision tree is a widely used machine learning model [55] which has several advantages. For instance, we can cite the simplicity of interpretation and explanation of data because it allows visualized decision-making [54]. Finally, they are often used to solve classification and regression problems. On the other hand, decision trees have many disadvantages such as their propensity to overfit the training data too precisely. Moreover, the complexity of the decision trees increases, and they become difficult to interpret when they are deep. Finally, decision trees are complex, and their performance is inferior to that of other algorithms (SVM, kNN) when applied to large datasets [56][57].

- **Extremely random trees (ExtraTree)**

According to [52] , extremely random trees make it possible to manage non-linear data because they do not require any functionality modification, like decision trees. They are easy to understand, interpret and visualize. However, extremely random trees have some limitations because they cannot easily adapt to the training data. They have reduced interpretability and higher calculation time, compared to decision trees. Finally, they are sensitive to outliers.

Table 2. The existing indoor and outdoor localization approaches

Authors	Technical	Meta-heuristic Optimization	Technology	Measurement Technique	Results	
					indoor	outdoor
Perkovic et al. [44]	DNN/SNR	No	LoRaWAN	RSSI and SNR	Precision98.8%	-------
					Error --------	---------
Zeaiter [45]	------	No	LoRa	AoA	Precision------ Error5% if heigh signal 12 %if signal low	
Yadav et al. [46]	SVR, ANN, KNN	Nash Q-learning			Error<1,5m	0,5m< error Avrage <1,5m
Althobaiti et al. [47]	Hybrid cooperative localization			RSS or TOA		
Kim et al. [48]			LoRaWAN	RSSI	Error 1.6 m in LOS 3.1 m in extreme NLOS condition	
Purohit et al. [49]	ANN CNN		LoRaWAN	RSSI	Error1.324271 Error 1.804363	284.78475 215.06072
Tinh and Mai [50]	KNN, DNN RF		Wi-Fi	RSSI	1.10	
Li and Hu [51]	-----	Kalman filter	------	------	Precision 2%	Error 2m
Corte-Valiente et al. [7]	------	Fngerprinting	Wi-Fi	RSSI	Precision 71.28% Error 1.9 m	------- 0.49m

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• **Random Forests**

Random forest algorithms essentially take a collective decision employing several decision trees [58]. According to [54], the random forest algorithm allows for reducing overfitting by combining predictions made up of multiple decision trees, which enhances the generalization of new data by the used model. Besides, compared to ensemble decision trees, random forests are less sensitive to outliers and noise in the data, which produces more stable and reliable solution predictions. Compared to the decision tree-based algorithm, the random forest algorithm does not require the randomization or scaling of data, which simplifies data preprocessing.

• **Neural Networks – NN**

Neural networks are powerful tools used to model complex data that can capture complex and nonlinear relationships between several variables [53]. These algorithms can learn hierarchical representations of data and relevant features from raw data. However, neural networks are complex to train and require large amounts of data to avoid overfitting.

• **Forward Neural Network**

Feedforward neural networks are powerful tools used to model complex data that can capture complex, nonlinear relationships between variables [4]. Since information propagates directly from the beginning to the end of the network without feedback loops, it is often easy to interpret the decisions made by a feedforward neural network. Therefore, feedforward neural networks can be effectively utilized in various machine learning tasks, especially when model complexity must be controlled. Like other algorithms, they have several limitations. In fact, due to their linear nature and direct data propagation, feedforward neural networks are sensitive to non-linear data. Additionally, they show high complexity when applied in sequential modeling tasks as they do not capture sequential dependencies efficiently [59]. Like any machine learning model, these networks can be sensitive to mislabeled or noisy data, which degrades their performance. Generally, neural networks and SVMs exhibit good performance when dealing with multi-dimensional and continuous functionalities [53].

4. Conclusion

In this article, the different localization technologies and machine learning and optimization techniques applied to solve mobile localization problems in a smart city were first detailed. Then, the localization issues were described. The various technological advantages and challenges in this field were, subsequently, analyzed. Then, the various localization techniques were discussed, and the existing localization algorithms were classified. Then the existing machine-learning approaches were detailed, while the last section focused on machine-learning-based localization solutions. The literature survey revealed that there are various location-related optimization algorithms: bio-inspired methods, meta-heuristics, and contemporary machine-learning techniques. These algorithms play a crucial role in increasing the accuracy and efficiency of the localization systems in various environments. Each section ended with tables comparing the existing techniques.

The research contribution is to present the different interests and issues related to localization in smart cities. Besides, it describes the different indoor and outdoor location technologies, enumerates their advantages and disadvantages, and compares indoor and outdoor localization technologies. This manuscript also classifies the communication networks in smart cities and shows the characteristics of each type. Additionally, it details the various machine-learning algorithms used to solve localization problems. The performed analysis and the state-of-the-art showed that previous works did not introduce an ideal solution allowing precise localization, without seams between the interior and exterior of the moving elements of a smart city whose energy consumption is compatible with mobile wireless connected objects having low energy capacity and taking advantage of the enormous quantities of data produced by the first IoT networks in smart cities. Therefore, our future research work will focus on the exploitation and processing of this massive data using bio-inspired methods, meta-heuristics, and new machine-learning techniques. Our objective is to work on a new intelligent IoT network qualified as AI-IoT. In the future, we can further explore optimization algorithms based on metaheuristic-based machine-learning techniques. These algorithms use either weighting principles, i.e. adding an importance weight to each objective to optimize or hybridize several algorithms. From this study, we will establish an approach relying on metaheuristics to solve localization optimization problems.

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