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Advances in Wireless Sensor Network Localization Techniques in Smart Cities; A Review

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Abstract

The challenges associated with Wireless Sensor Networks (WSN) techniques in smart cities conceive the ideas of this review research. These challenges are but not limited to; Indoor Environments where GPS are not reliable, Energy Constraints, Network Scale and Complexity. A review of WSN localization algorithms for smart cities identifies key techniques like range-based (e.g., Time-of-Arrival, Time-Difference-of-Arrival, Angle-of-Arrival, Received-Signal-Strength) and range-free (Centroid-base, Distance-Vector Hop, Approximate-in-Triangulation, Centroid-Base, Multi-Dimensional-Scaling) methods, which determine node positions using known anchor nodes or cooperative localization. Recent approaches often take the advantages of combining the Software Defined Network (SDN) and Machine Learning (ML) to improve network accuracy and reduce energy consumption in the complex smart cities. However, some factors like; Anchor Node Availability, Application Requirements, Sensor Density and Distribution influence the algorithms choice to mitigate in the above-mentioned challenges. This paper explores and presents a survey of current localization techniques for wireless sensor networks. In this survey, we present the entire localization process and classification of localization methods and algorithms. The merits and demerits of each localization were outlined and comparatively compared to determine its suitability in choices of network designs.

Keywords: Smart Cities; WSN; Localization Algorithms; Range Free Localization; Range Base Localization

1. Introduction

Wireless Sensor Network (WSN) is a connection of distributed autonomous sensors which are wirelessly networked with the ability of exchanging information for the purpose of monitoring our physical environment such as temperature, pressure, motion, sound, vibration, etc [1], [2].

These sensors, often tiny and battery-powered, can detect various environmental conditions like temperature, pressure, humidity, and more. WSNs are used in diverse applications, including military surveillance, agricultural monitoring, heath/patient monitoring, environmental, industrial monitoring, smart homes and cities [3]. There is a rapid growth and overwhelming interest in WSN, however, outside its limited memory processing and low power, it is associated with impending challenges such as; node deployment, energy efficiency, network security, hardware faults, scalability and data management [4].

A WSN consist of hundreds to millions of nodes that make the installation of Global Positioning System (GPS) on each sensor node expensive and moreover GPS will not provide exact localization mostly in an indoor environment [5]. Manually configuring location reference on each sensor node is also not possible in the case of dense network which are foreseen in most cases. This gives rise to a problem where the sensor nodes must identify its current location without using any special hardware like GPS and without the help of manual configuration. Localization techniques make the deployment of WSNs economical [6]. Most of the localization techniques are carried out with the help of anchor node or beacon node, with known location. Based on the location information provided by the anchor node or beacon node, the target nodes can be determine using various localization algorithms [7].

2. Localization

Localization algorithms for Wireless Sensor Networks (WSN) are essential for determining the geographical positions of sensor nodes, enabling applications like geographic routing and data dissemination [8]. These algorithms leverage anchor nodes (known location) and various techniques to determine the positions of other sensor nodes. The choice of algorithm depends on factors like network architecture, sensor density, and application requirements [9]. The task of determining physical coordinates of sensor nodes in WSNs is known as localization or positioning and is a key factor in today's communication systems, that's to estimate the place of origin of events [10]. WSN localization network contains anchor nodes, displaced nodes, and a central server [11]. In localization, to determine the absolute location, a few nodes called anchors need to know their exact locations, and all the other nodes are completely located using the anchors' known location [12]. GPS-based localization is a combination of sensor fitted with a GPS receiver. This combination of a sensor (node) fitted with a GPS receiver, a small set of it can act as a reference beacon node [13]. These reference nodes must define an absolute coordinate system in which other nodes rely on to estimate their unknown locations [14]. Hence, Localization is the process of determining the position of a node (beacon or target) sensor within the network. The accuracy of localization significantly impacts the performance of smart city applications such as smart transportation, disaster management, and energy optimization.

The coverage model of a WSN system is based on the distance from the nearest point of interest. The localization algorithms are used to examine the coverage of the sensors and estimate their locations to the base station [15]. In order to improve scalability and reduce the overall costs due to changes in topology a Location-based Routing (LR) protocols that rely on the position of data

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is used [16]. Likewise adequate measure should be put in place in management of the energy and power at the nodes, which intends to extend the lifespan of the network, depending on where each node is located in the network [17]. Moreso, for effective communication, the nodes in the network should be aware of their neighbours and their respective exact positions. The exact position of a node is a great challenge in real life application such as object tracking [18].

In typical WSN deployments, sensor nodes are often placed randomly. While Global Positioning System (GPS) technology provides the most accurate and reliable method for determining the exact positions of these nodes, equipping each sensor node with a GPS module presents several challenges [19]. Firstly, the cost of integrating GPS into every sensor node becomes prohibitively expensive, especially for large-scale networks. Secondly, GPS modules have high energy consumption, which is problematic for sensor nodes that are designed to operate with minimal power. Due to these limitations, using GPS for all sensor nodes in a WSN is often impractical. One solution to the GPS issue in wireless sensor networks (WSNs) is to use a few sensor nodes equipped with localization modules to help determine the positions of other nodes. This technique is known as node localization [20]. In this approach, the sensor nodes with localization modules are called beacon nodes. These beacon nodes know their exact locations, while the other nodes, which do not know their locations, are referred to as unknown nodes. Using the location information from the beacon nodes, the network can estimate the positions of the unknown nodes. This method reduces both cost and power consumption as only a small number of nodes need to be equipped with the more expensive, high-power localization modules [21].

However, node localization in WSNs is challenging due to the presence of obstacles, multipath effects, and energy constraints. Existing localization methods, such as Global Positioning System, are not suitable for WSNs due to their high energy consumption and limited availability in urban canyons (steep, narrow, rocky walls), example; Grand Canyons (Arizona), Fish River Canyons (Namibia), Colca Canyons (Peru) and Taroko George Canyons (Taiwan). Essentially, knowing the position of each sensor nodes are paramount as data received with the knowledge of their respective known location are used in making rightful decision [22]. However, each WSN should have a GPS, but due to its complexity, cost and energy consumption as earlier enumerated above, we can use a known location sensor node to estimate the location of an unknown sensor node using various types of algorithms that we are going to discuss later [18]. Hence the method of determining the position of a node assigned in a network is known as localization [23].

2.1. Localization in smart cities

Localization is a key technology in smart cities, and is used to predict the location of objects in both indoor and outdoor environments. It's used in many smart city applications, including: Vehicular communication systems, The Internet of Things (IoT), and Integrated Sensing and Communication (ISAC) technologies [24], [25]. Localization is the process of predicting the location of an object, while positioning is the raw data that expresses the object's position.

Localization techniques are typically divided into indoor and outdoor localization [26]. However, achieving precise localization can be challenging due to Non-Line-of-Sight (NLOS) conditions and uncertainties in wireless transmission parameters [25]. Smart cities also use Location-Based Services (LBS) to provide information to individuals based on their location. For example, an LBS provider might use a person's location data to suggest the nearest restaurant, Automated Teller Machine (ATM), or retail store [27].

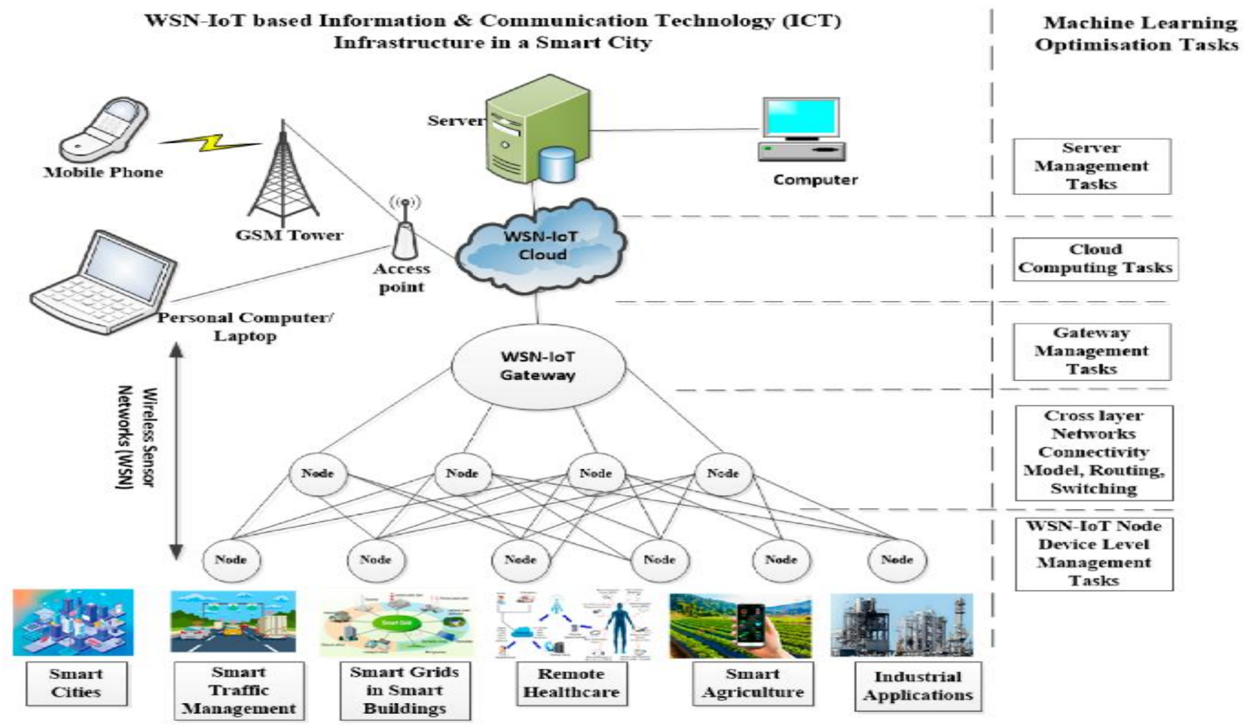

Figure 1: WSN-IoT applications in a smart city [28]

2.2. Smart city technology

A smart city is a municipality that uses information and communication technologies to increase operational efficiency, share information with the public and improve both the quality of governance [29]. Smart cities use data analysis and smart technologies to: Optimize city functions, Promote economic growth, Improve the quality of life for citizens, Reduce risk, and Provide better services for citizens [30], [31]. While the exact definition varies, the overarching mission of a smart city is to optimize city functions and drive economic growth while improving quality of life for its citizens using smart technology and data analysis [32]. Value is given to the smart city based on what they choose to do with the technology, not just how much technology they may have [33]. Smart cities use a combination of the internet of things devices, software solutions, User Interfaces (UI) and communication networks. However, they rely first and

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foremost on the IoT. The IoT is a network of connected devices -- such as vehicles, sensors or home appliances -- that can communicate and exchange data [34]. Data collected and delivered by the IoT sensors and devices is stored in the cloud or on servers. The connection of these devices and use of data analytics (DA) facilitates the convergence of the physical and digital city elements, thus improving both public and private sector efficiency, enabling economic benefits and improving citizen's lives [29], [32].

3. Related Works

This work reviews the various localization techniques used in WSNs, their application in smart cities, challenges they face, and the evolution of hybrid methods combining multiple techniques to improve node localization accuracy and energy efficiency. Localization of fixed or mobile wireless sensors in wireless sensor networks is a delicate issue that has attracted the attention of many researchers [28]. Indeed, a good estimation of the distances between different wireless sensors allows to derive their precise locations in the network. An ideal solution for locating these wireless sensors is to equip them with localization devices such as GPS. However, this solution is limited in the following areas: Indoor/Urban Canyon Limitations: GPS signals can be weak or blocked in indoor environments, urban canyons, or areas with dense foliage, leading to inaccurate or unavailable location information. Power Consumption: GPS modules can consume significant power, which can be a concern for battery-powered sensor nodes with limited energy resources. Cost: GPS modules can add to the overall cost of the sensor node, which can be a significant factor in large-scale WSN deployments [35]. So, it is not possible to replace the batteries of these wireless sensors when they are discharged. On this necessity, [36] propose an Efficient Anchor Free Localization Algorithm (EAFLA). Despite the grouping of nodes into clusters (or sub-networks), existing anchor-free localization algorithms suffer from a low rate of node localization, low localization accuracy, and high energy consumption. Regardless the topology of each cluster, the algorithm allows localization of all wireless sensors with a very low localization error rate and consumes less energy.

In recent years, optimization algorithms have garnered significant attention as a means of enhancing the WSN node localization. [37] presents an in-depth exploration of the necessity of localization in WSN nodes, and offers a comprehensive review of the optimization algorithms used for this purpose. This review encompasses a diverse range of optimization techniques, including evolutionary algorithms, swarm intelligence, and metaheuristic approaches [38]. Key factors such as localization accuracy, scalability, computational complexity, and robustness were systematically evaluated and compared across various optimization algorithms. Additionally, the study sheds light on the strengths and limitations of each optimization approach and discusses their applicability in different WSN deployment scenarios [39]. The insights provided in their review serve as valuable resources for researchers and practitioners seeking to optimize WSN node localization, thus promoting the efficient and reliable operation of WSNs in diverse real-world applications.

Many applications of WSNs, such as environmental monitoring, security monitoring, health monitoring, and agriculture, precise location of nodes is crucial. As a result of this, [40] propose a novel and efficient way to solve this problem without any regard to the environment, as well as without predetermined conditions. This proposed method is based on new proposed Nutcracker Optimization Algorithm (NOA) [41]. Utilizing their proposed algorithm, it is possible to maximize coverage rates, decrease node numbers, and maintain connectivity. They activate several other algorithms, such as Grey Wolf Optimization (GWO), Kepler Optimization Algorithms (KOA), Harris Hawks Optimizer (HHO), Gradient-Based Optimizer (GBO) and Gazelle Optimization Algorithm (GOA). The node localization was first tested in Istanbul, Turkey, where it was determined to be a suitable study area. As a result of the metaheuristic-based approach and distributed architecture, the study is scalable to large-scale networks. Among these metaheuristic algorithms, NOA, KOA, and GWO have achieved significant performance in terms of coverage rates (CR), achieving coverage rates of 96.15%, 87.76%, and 93.49%, respectively. In terms of their ability to solve sensor node localization problems, these algorithms have proven to be effective.

The well-known Distance Vector Hop (DV-Hop) algorithm is a suitable solution for localizing nodes having few neighbor anchors. However, existing DV-Hop-based localization methods have not considered the problem of anchor breakdown which may happen during the localization process. This is a significant concern, especially in dynamic environments where network conditions can change. Traditional DV-Hop methods often assume that anchor nodes are always available and reliable. They don't explicitly incorporate mechanisms to handle failures or adjust the localization process in case of anchor breakdowns. The reliance on all anchor nodes can make DV-Hop-based localization algorithms vulnerable to failures. If a critical anchor fails, the localization process can be severely impacted. In order to avoid this issue, an Online Sequential DV-Hop algorithm was proposed by [42] in their paper to sequentially calculate positions of nodes and improve accuracy of node localization for multi-hop wireless sensor networks. The algorithm deals with the variation of the number of available anchors in the network. They developed an algorithm that can dynamically adapt to changes in the network, including anchor breakdowns.

These methods often employ online sequential computation to update the position estimates of nodes as anchor nodes fail. They noted that DV-Hop algorithm was used in their article to process localization of nodes by a new optimized method for the estimation of the average distance of hops between nodes. Their proposed localization method is based on an online sequential computation, compared with the original DV-Hop and other localization methods from the literature, simulation results prove that the proposed algorithm greatly minimizes the average of localization error of sensor nodes [43]. Equally, other researchers have proposed using only a subset of anchor nodes for localization, reducing the impact of individual anchor failures. These methods often employ optimization techniques to select the best subset of anchor nodes for a given network configuration [44]. Other approaches focus on improving the accuracy of hop count estimation, which can help to mitigate the impact of errors introduced by anchor failures. These methods often utilize techniques like weighted hop counts or improved communication protocols [45]. Some algorithms use a recursive approach, where nodes are localized sequentially, and the localized nodes themselves can be used as anchors for subsequent localization steps. This can provide a more robust localization solution in the face of anchor breakdowns [46].

The effects of ranging error and localization geometry on localization error, [47] introduce a simple measure to evaluate the Geometry of Reference Triangle (GRT). To improve localization accuracy and precision, they propose an Adaptive Range-Based Localization (ARBL) algorithm that is based on trilateration and reference node selection. In ARBL, the GRT values are calculated for each 3-combination of a preselected reference node set, based on which the combinations are selected [48]. The algorithm exploits these reference node 3-combinations aiming to find the best ones at a given time using selection criteria that is based on ranging error and localization geometry. This a process where the "best" combination of reference nodes (or anchors) for localization is chosen based on factors like the expected ranging error and the geometry of the resulting location estimates. This approach aims to improve localization accuracy by selecting reference nodes that provide a more robust and precise location estimate, even in the presence of ranging errors [49] [50]. The simulation and experimental results indicate that the proposed algorithm reduces localization error considerably. This shows that it is possible to achieve sufficient localization accuracy using range-based trilateration localization, even based on the RSSI in challenging outdoor conditions, by employing applicable techniques and information.

The Extended Kalman Filter (EKF) has received abundant attention with the growing demands in smart cities and robotic localization [24], [47]. The EKF algorithm is more realistic in non-linear systems, which has an autonomous white noise in both the system and the estimation model. Also, in the field of engineering, most systems are non-linear. Therefore, the Extended Kalman Filter (EKF) is a nonlinear version of the Kalman filter used to estimate the position of sensor nodes. It's particularly well-suited for WSN applications where the system dynamics and measurements might be nonlinear. The EKF extends the traditional Kalman filter by using a linearization of the nonlinear system model to estimate the state (position and other relevant variables) of the target nodes [51]. The core function of EKF in WSN localization is to estimate the position of sensor nodes, which might be mobile or fixed, within the network. It equally addresses the challenge of nonlinear system models and measurements that are common in WSNs, such as sensor noise, varying environmental conditions, and signal propagation. The EKF attracts more attention than the Kalman Filter (KF), it is well-suited for applications where the system model or measurements are nonlinear, unlike the standard Kalman filter which is limited to linear systems. The recursive nature of the EKF allows it to efficiently incorporate new information and update its state estimates over time [52]. The authors propose an EKF-based localization algorithm by edge computing, and a mobile robot is used to update its location concerning the landmark. This localization algorithm aims to achieve a high level of accuracy and wider coverage. The proposed algorithm is helpful for the research related to the use of EKF

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localization algorithms. Simulation results demonstrate that, under the situations presented in their paper, the proposed localization algorithm is more accurate compared with the current state-of-the-art localization algorithms.

The Distance Vector Hop Localization Method (DVHLM) is another technique used to address the node dislocation issue in real-time networks, [20] proposed method combines trilateration and Particle Swarm Optimization techniques to estimate the location of unknown or dislocated nodes. Their methodology includes four steps: coordinate calculation, distance calculation, unknown node position estimation, and estimation correction. To evaluate the proposed method, they conducted simulation experiments and compared its performance with state-of-the-art methods in terms of localization accuracy with known nodes, dislocated nodes, and shadowing effects [53]. The results demonstrate that DVHLM outperforms the existing methods and achieves better localization accuracy with reduced error. The article provides a valuable contribution to the field of WSNs by proposing a new method with a detailed methodology and superior performance.

As the global-positioning-system (GPS) is unreliable in indoor scenarios, some methods in WSNs-based indoor localization have been developed. Path loss model-based can be useful for providing the power-distance relationship, the distance-based indoor localization. Received Signal Strength Indicator (RSSI) has been commonly utilized and proven to be a reliable yet straightforward metric in the distance-based method. To overcome the complexity of indoor localization, [54] applied the standard distance-based methods, which are trilateration and min-max or bounding box algorithm. Trilateration uses distance measurements from multiple known points to calculate a precise location, while the min-max algorithm uses a bounding box approach, creating a rectangular area that likely contains the target [55], [56]. The authors used the RSSI values as the localization parameter from the ZigBee standard, utilized the general path loss model to estimate the traveling distance between the transmitter (TX) and receiver (RX) based on the RSSI values [57]. The measurements were conducted in a simple indoor lobby environment to validate the performance of the proposed localization system. The results show that the min-max algorithm performs better accuracy compared to the trilateration, which yields an error distance of up to 3m. By these results, they conclude that the distance-based method using ZigBee standard working on 2.4 GHz center frequency can be reliable in the range of 1-3m. This small range is affected by the existence of interference objects (IOs) leading to signal multipath, causing the unreliability of RSSI values. These results can be the first step for building the indoor localization system, with low-cost, low-complexity, and can be applied in many fields, especially indoor robots and small devices in internet-of-things (IoT) world’s today.

Outdoor location services have thrived over the last couple of decades because of well-established platforms for both of these components (e.g. Google Maps for mapping, and GPS for positioning). In contrast, indoor location services haven’t caught up because of the lack of reliable mapping and positioning frameworks. Wi-Fi positioning lacks maps and is also prone to environmental errors. A Deep Learning based wireless localization algorithm that can overcome traditional limitations of RF-based localization approaches (like multipath, occlusions, etc.) was presented by [58]. DLL was augmented with an automated mapping platform, called Map Find. Map Find constructs location-tagged maps of the environment and generates training data for Deep Learning Localization (DLL). Together, they allow off-the-shelf Wi-Fi devices like smartphones to access a map of the environment and to estimate their position with respect to that map [59]. During our evaluation, Map Find has collected location estimates of over 105 thousand points under 8 different scenarios with varying furniture positions and people motion across two different spaces covering 2000 sq.ft. DLL outperforms state-of-the-art methods in Wi-Fi-based localization by 80% (median & 90th percentile) across the two different paces.

4. Localization Process

The process of localization in WSN involves the determination of the exact distance, position of each sensor nodes in a network and the different localization techniques used [60]. Distance or range involves computing measured distances from points A to B, while positioning involves estimating the geographic coordinates of sources in a network from the mutual distances between devices [61]. During the process of localization, it is the area of interest that sensor nodes are deployed using any of these node deployment strategies namely; random deployment, grid-based deployment, cluster-based deployment, hierarchical deployment and deterministic deployment [62]. During the process of nodes deployments, a peculiar attention or rather consideration is made in terms of coverage area, connectivity, energy efficiency, cost and the nature of the environment in question [63]. The following node deployment techniques can be used depending on the nature of network of the designer’s interest; drop and forget (nodes are dropped from aircraft), manual, robotics deployment and self-development [64]. The deployment metrics will evaluate the effectiveness and efficiency of the node deployment metrics [65].

To achieve this, we can use any of the following metrics; coverage metrics, connectivity metrics, energy-efficient metrics, quality of service metrics, reliability metrics, scalability metrics, cost metrics and others. In addition, the following tools can be used, such as simulation software (e.g. NS-2, OMNet ++), deployment algorithm (e.g. Genetic Algorithm, Particle Optimization) and node placement optimization (e.g. Linear Programming, Non-Linear Programming) [66]. During the process of anchor node placement and measurement of data collection, the anchor nodes (nodes with known positions) are relatively placed within the network, each of the nodes collect or rather exchange information (data) with the neighbouring node through any of the following process; Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA), Phase Difference of Arrival (PDOA) and Angle of Arrival (AOA) [67]. Nodes estimate their locations using localization algorithm as well as refine their estimated locations through iterative algorithms [68]. Some of the popular ones are; Range-based Algorithms, Range-Free Algorithm, Hybrid Algorithm, Distributed Localization Algorithm, Centralized Localization Algorithm and Machine Learning-Based Algorithm [69]. While iterative localization algorithms are; Kalman Filter (Recursive state estimation), Particle Filter (Monte Castro-based localization), Extended Kalman Filter (Non-linear state estimation), Unscented Kalman Filter (Non-linear state estimation) [70]. It is of importance to note that when choosing any of the algorithm mentioned above, the following factors are designer's standard in making choices; network size and complexity, energy efficiency, computational resources, environmental condition and accuracy [71].

In localization verification, nodes verify their estimated locations using various techniques such as; consistency verification (verify location estimates against measured data), boundaries checking, neighbour verification, redundancy verification and statistical verification (subjection to any of the statistical method, e.g. hypothesis testing) [72]. However, to achieve the best standard practice, it is advised to use multiple verification techniques, with optimized verification algorithms to navigate the network dynamics in monitoring the localization performance [73]. WSNs update node's locations due to changes in network topologies and environmental conditions, this can be periodically, on request basis and event-driven which are triggered by specific events, e.g. node redeployment [74]. To overcome the challenges such as; network overhead, scalability and energy efficiency the designer should be able to incorporate a better location update techniques like predictive modeling which relies on the use of historical data to predict future locations [75]. Other techniques are Kalman-Filter which estimates the location based on noisy environments, Particle Filter which make use of Monte Carlo-based location estimation and finally the fingerprinting technique which uses pre-measured location specified-data [37].

Figure 2: Overview of Localization Process

5. Classification of Localization Techniques in WSN

Localization techniques can be classified into two categories namely; target/source (transmitter node) and node-based/anchor (receiver node) localization. This target/source localization can be further classified into single-target localization and multiple-target localization. Target/source localization technique can be used for both indoor and outdoor localization applications such as; vehicles tracking, including ships and large sea animals (sharks and whale) tracking, military weapon tracking and aircraft tracking. On the other hand, node-based localization technique can collectively determine a sensor's position relative to each other node using any base distance measurements (Euclidean, Non-Euclidean, Hyperbolic, Elliptical, Differential, Topology and Analytical geometry). Node-based localization technique can be classified into; proximity/range-free localization, range-based localization and hybrid-based localization. Their only difference is based on the information they use for localization. Range-based technique uses range measurement while range-free techniques use the content of the message. Range-based localization measures the proximity in terms of hop-count estimated distance to a few landmark sensor nodes with known location.

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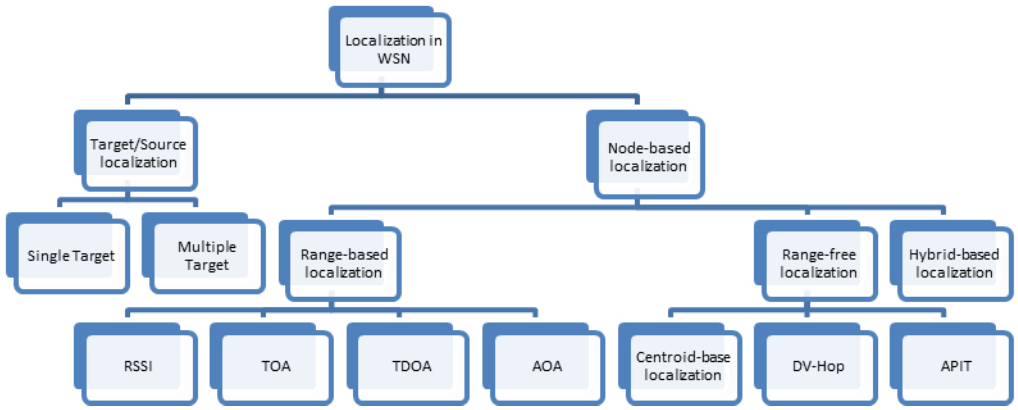

Figure 3: Classification of Localization Techniques in WSN

Range-free localization requires no measurement on distance or angle among the nodes, while hybrid-based localization is a combination of range-free and range-base localization techniques as well as integration of multiple sensors e.g, GPS, Wireless Fidelity (Wi-Fi), Bluetooth. Range-based localization can be furthermore classified into; Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AOA), while range-free localization is classified into pattern matching localization and hop-count based localization. Other localization-based mechanisms are; GPS based localization, indoor localization, sensor network localization, absolute localization, relative localization and triangulation localization.

6. Range-Free Localization

Range-free or Proximity localization is a method used to estimate the location of a target node from the reference node or anchor node without measuring the exact distance between the two nodes [76]. The operation principle of this method is based on anchor node and target node connectivity and proximity. The proximity factor is determined by the ability of the anchor node to demodulate and decode the packet transmitted by the target node. Range-free localization methods do not require direct distance or angle measurements but instead rely on indirect methods such as proximity to reference nodes or geometric constraints [1]. Messages are exchanged between neighbours, and this approach requires no extra bandwidth. One of the advantages of this approach is estimation of the position of the node with reasonable accuracy without additional hardware costs. The low cost of this approach is dependent on precision. The proximity measurements indicate whether two devices are connected or in-range. In this case, only a small percentage of the devices have knowledge of their location in the coordinate system. The coordinates are made known to the nodes using the reference points. If the nodes are within the range, it is set to 0 and if the nodes are not observable, the proximity value of the nodes is set to 1. In this case, a threshold value is set which determines the range of the node. If the signal amplitude achieved is higher than the threshold, it is considered that the nodes are both within range and outside range. Below, we are going highlight on the various type of range-free localization techniques as our research work is focused on range-based localization techniques.

6.1. Centroid-Based Localization

Centroid-based localization is a range-free positioning technique that estimates the location of a node by averaging the coordinates of known anchor nodes (nodes with known locations). Unlike range-based methods that require distance measurements, centroid-based localization relies on the relative positions of anchor nodes to estimate the location of unknown nodes [77]. This method uses a set of reference nodes to estimate the position of a target node by calculating the centroid of the positions of nodes within a given distance. A subset of nodes in the network have known locations (anchor nodes). The unknown node calculates its location by averaging the coordinates of the anchor nodes within its communication range. In some implementations, weights can be assigned to anchor nodes based on factors like distance or signal strength, to improve accuracy [78]. Centroid-based localization assumes that a node's location is approximately equal to the centroid (geometric center) of its neighboring nodes. The technique relies on the connectivity information between nodes to estimate their locations. Centroid-based localization may not perform well in scenarios with sparse or poorly distributed anchor nodes but relatively simple to implement compared to range-based localization techniques.

6.2. Distance Vector-Hop (DV-Hop) Localization

Distance Vector-Hop (DV-Hop) localization is a distributed, range-free localization algorithm that estimates the position of unknown nodes based on the number of hops between them and known anchor nodes, without requiring direct distance measurements [79]. The algorithm is distributed, meaning each node participates in the localization process without requiring a central authority or coordinator. The core concept is to estimate the distance between unknown nodes and anchor nodes (nodes with known positions) by counting the number of hops (or links) between them. This technique determines the location of nodes by calculating the average number of hops from the target node to reference nodes. Each hop corresponds to an approximate distance. DV-Hop just like other hop count localization techniques uses the number of hops (i.e., transmissions) between anchor nodes to estimate distances and locate target nodes [80]. In this case, each sensor node calculates its distance based on the minimum hop number and average distance with respect to the anchor node. After that, the distance can be computed between the target node and the anchor node by multiplying the minimum hops with the average distance of each hop. Finally, each node estimates its position coordinates using different estimation techniques, such as triangulation, trilateration, maximum likelihood estimators and so on. It achieves this in two stages; offline and online mode. In an offline mode, a unique identification numbers are assigned to selected anchor nodes (1, 2 & 3) as shown in Figure 4 below, which transit these unique nodes to the target node (4, 5, 6, 7, 8 & 9). The hop-count is set to zero or initialize it from zero at the beginning of the transmission. This value is incremented by other neighbours when they receive it and then they re-broadcast again.

Therefore, if the target node receives a message from the anchor node, it stores the coordinates of the target node and increment the hop count by one.

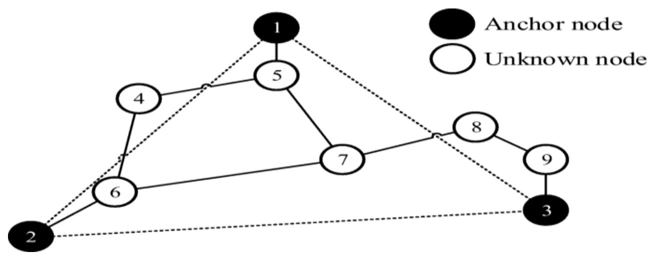

Figure 4: Example of DV HOP Localization [81]

However, each of the target nodes that received the unique identification number and stored it will increase the hop-count, this will be repeated until all target nodes have received the broadcasted unique identification number. The unique identification number carries all the necessary information of the transmitting anchor nodes used in estimation of the target nodes. Actually, if the target node receives a message from the same target node, it first checks the hop number and increment it directly and then compare it with the stored one if it is less, it updates its value and rebroadcast it with the new hop value otherwise, it drops the message. At the end of this stage, all nodes, both anchor and target nodes, will have the minimum hop counts with respect to all anchor node in the network. DV-Hop is relatively simple to implement and computationally efficient, making it suitable for resource-constrained WSNs, whereas it can suffer from poor localization accuracy, especially in scenarios with uneven node distribution or high noise levels. Researchers like [82], [83] [84]have proposed various optimization strategies to improve the accuracy of DV-Hop, such as improving hop count calculation methods, adding weights to the mathematical model, or using optimization algorithms. Similarly, Amorphous, Hop-TERRAIN and DV-Hop max employs the following techniques in distance estimation in range-free localizations; Its benefits ranges from; scalability, accuracy, robust to multipath effects and low computational complexity. However, its challenges are not left out as it encounters node mobility, anchoring strategy, security risk, irregular network topology and accuracy in hop-count estimation.

6.3. Approximate Point-In-Triangulation (APIT)

Approximate Point-in-Triangulation (APIT) is a localization algorithm that uses a non-localized, iterative approach to estimate the location of nodes by triangulating the environment using beacon transmissions from anchor nodes [85]. This is another range-free localization technique that uses triangles formed by anchor nodes to estimate the locations of unknown nodes [86] [81]. APIT employs an area-based approach, meaning it determines the location of a node by identifying the region or area where it potentially resides. The core principle of APIT involves triangulating the environment using anchor nodes (nodes with known locations). A node determines its location by performing a PIT test, which checks if it lies inside or outside triangles formed by three anchor nodes. By iteratively refining the area based on PIT tests using combinations of anchor positions, APIT narrows down the estimated area where a node can potentially reside, leading to more accurate location estimates. The APIT protocol generally consists of four phases: beacon exchange, PIT test, APIT aggregation, and Center of Gravity (COG) estimation.

- **Beacon Exchange:** Each node exchanges information about the connectivity of its neighbors to the anchors.
- **PIT Test:** A node determines if it is inside or outside a triangle formed by three anchor nodes based on the distances to the triangle's vertices.
- **APIT Aggregation:** This phase determines the triangles in which the unknown node exists and aggregates the information to constrain the location.
- **COG:** The node estimates its location as the center of gravity of the overlapping area.

Here's a step-by-step overview of this localization technique: (1) Anchor node placement: Anchor nodes with known locations are placed in the network. (2) Triangle formation: Three anchor nodes form a triangle. (3) Point-in-triangulation test: An unknown node determines whether it is inside or outside the triangle. (4) Location estimation: The unknown node estimates its location based on the number of triangles it is inside. The key differences between Anchor-based Pairwise Triangulation and Approximate Point-In-Triangulation are triangulation approach and location estimation. Anchor-based Pairwise Triangulation uses pairwise triangulation, while Approximate Point-In-Triangulation uses a point-in-triangulation test. While on their process of location estimation, Anchor-based Pairwise Triangulation estimates the location by calculating the intersection of triangles, while Approximate Point-In-Triangulation estimates the location based on the number of triangles the node is inside.

6.4. Connectivity-Based Localization

Connectivity-Based Localization determines sensor node locations based on the network's connectivity structure, specifically whether nodes can directly communicate with each other (binary 1) or not (binary 0), rather than relying on distance measurements [87]. This relies on the connectivity information between nodes, inferring distances based on the presence of links. Connectivity-based localization assumes that nodes can communicate with each other if they are within a certain communication range (R) by analyzing the connectivity patterns between nodes, the technique can estimate the locations of nodes [88], [89]. Unlike range-based localization techniques that estimate distances or angles, connectivity-based methods focus on the presence or absence of direct communication links between nodes. Unlike range-based localization techniques that estimate distances or angles, connectivity-based methods focus on the presence or absence of direct communication links between nodes. A sensor node is considered connected to another if it can directly transmit and receive data from it within its radio range; otherwise, they are not connected (binary 0 or 1). The distance between nodes is represented by the number of hops (or intermediate nodes) required to reach one node from another. Various algorithms are used to estimate the average hop distance and, consequently, the location of the

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nodes. Connectivity-based localization can be simpler to implement and more energy-efficient than range-based methods, as it doesn't require complex distance measurements. The accuracy of connectivity-based localization can be lower than range-based methods, especially in environments with obstacles or varying radio range.

6.5. Multidimensional Scaling (MDS) localization

Multidimensional Scaling (MDS) localization a range-free localization technique that leverages the connectivity information between nodes to estimate their positions, rather than relying on direct distance measurements. It works by mapping the topological relationships between nodes into a geometric space [90]. MDS algorithms utilize the network topology, specifically the connectivity (or lack thereof) between nodes, to infer their relative positions. MDS is a technique that reduces the dimensionality of data while preserving the distances between data points. In WSN localization, it maps the connectivity information (e.g., hop counts) into a 2D or 3D space. MDS algorithms typically start with a distance matrix that represents the "distances" between nodes, often based on hop counts or other connectivity metrics. The MDS algorithm then maps these distances into a geometric space, where the relative positions of nodes are determined. While some MDS algorithms are range-free, some versions, like MDS-MAP, can leverage anchor nodes with known locations to map the relative positions to absolute coordinates [91] [92]. MDS algorithms rely on connectivity information, which is typically less resource-intensive to collect and transmit compared to range-based localization techniques. MDS localization can be relatively scalable, as the algorithm can handle a large number of nodes. MDS algorithms can be robust to some level of noise and inaccuracies in the connectivity information. MDS localization is generally less accurate than range-based localization techniques. The accuracy of MDS localization heavily depends on the network topology and the quality of the connectivity information. Some MDS algorithms can have high computational complexity, especially for large networks.

Table 1 below shows in clarity the strength and weakness of the four major range-free localization techniques in WSNs. It is desirable that Network Engineers should pay attention in choosing the techniques that best suits their purposes.

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Table 1 Comparison of the four major Range-free Localization Techniques

	Function	Centroid	DV-Hop	APIT	Connectivity-based
1	Algorithm type	Geometric: Uses geometric calculations to estimate location	Distance-based: Uses hop count to estimate distance and location	Geometric: Uses triangle-based calculations to estimate location	Graphed-based: Uses connectivity information to estimate location
2	Algorithm complexity	Low	Medium	High	Very high
3	Classification in terms of measurement type	Simple and coarse localization: Uses anchor node positions to estimate locations	Hop-based distance estimation	Triangle-based geometric	Graph-based localization
4	Accuracy	Low: Depends on node density & environmental factors	Medium: Depends on node density & environmental factors	High: Depends on node density & environmental factors	Medium: Depends on node density & environmental factors
5	Overhead	Low	Medium	High	Very-high
6	Hardware requirements	Low	Medium	Medium	High
7	Synchronization requirements	Low	Low	Low	Medium
8	Communication requirements	Low: Anchor node positions are broadcasted	Medium: Hop count information is exchanged between nodes	Medium: Neighbour information is exchanged between nodes	High: Connectivity information is exchanged between nodes
9	Computational Cost	Low	Medium	High	Very-high
10	Computational requirements	Low	Medium	High	Very-high
11	Processing requirements	Low	Medium	High	Very-high

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12	Data requirements	Low	Medium	Medium	High
13	Scalability	Medium	High	High	Very-high
14	Implementation	Easy	Moderate	Hard	Complex
15	Software complexity	Low	Medium	High	Very-high
16	Integration requirements	Easy	Moderate	Moderate	Hard
17	Suitability	Simple network	Medium-scale network	Medium-scale/moderate accurate network	Complex network
18	Location estimation method	Averaging anchor positions	Hop count-based distance estimation	Triangle-based testing	Graph-based optimization

7. Range-Based Localization

Range-Based Localization is a method of estimating the location of a target node by measuring the distance from multiple reference anchor nodes otherwise known as reference points using various ranging techniques. Range-based localization methods rely on measuring the distance or angle between nodes, using different signal propagation metrics. These methods usually require specialized hardware and more accurate measurements. We are going to explain this in details based on the following metrics. Sensor system localization algorithm evaluated the position of sensor with unknown nodes through the information obtained from a couple of nodes with the assistance of Global Positioning System (GPS), for example, distance and bearing estimations. Sensors with outright position data are referred to as beacon or anchors with GPS or through mounting anchors at factors with acknowledged coordinates.

7.1. Received Signal Strength Indicator (RSSI)

This is a range-based estimation technique and one of the readily available, low-complex technique for measuring the distance between a receiver (anchor) and a transmitter (target or unknown node). It is achieved by calculating the attenuation of the transmitted signal strength, which is often referred to as Received Signal Strength (RSS) based or Received Signal Strength Indicator (RSSI) ranging [94] [95]. This technique is widely used in wireless localization for range estimation as it requires no clock synchronization, no expensive hardware and in overall, a very low computational complexity is achieved with a tradeoff in its accuracy. RSSI are widely used in proximity detection as well as both indoor and outdoor localization in WSN. It is purely a distance and environmental dependent technique as the strength of the signal is affected as the distance increases. RSSI is a measure of the power level of a received radio signal, indicating how strong the signal is. Noise, multipath, interference and Non-Line of Sight (NLOS) affect the signal strength as well. Wireless Standards for RSSI measurements are: IEEE 802.11 (WLAN), IEEE 802.15.1 (Bluetooth), IEEE.15.4 (Zigbee) and LTE (4G & 5G). How it works: (1) Anchor nodes (nodes with known locations) transmit signals. (2) Other nodes (sensor nodes) measure the RSSI of these signals. (3) The RSSI values are used to estimate the distance between the sensor node and the anchor nodes. (4) By using the distances from multiple anchor nodes, the location of the sensor node can be calculated using techniques like trilateration or triangulation [96].

The principle on which this technique works is based on the fact that the Received Signal Strength (RSS) value in free space decreases proportionally with the squared distance ($d2$) between two nodes. The relationship between the transmitted power P_t and the received power P_r is given through Friis Equation (1), where G_t and G_r are the transmitter and receiver antenna gain, and where λ is the radio wave length.

$$P_r(d) = \frac{PtGtGr\lambda 2}{(4\pi 2)d2} \tag{1}$$

However, P_r is environmental dependent and could be easily affected by interference, multipath, reflection and diffraction while P_t, G_t and G_r are mostly device dependent which result in additionally incurred errors.

7.2. Time-Of-Arrival (TOA)

The Time-Of-Arrival (TOA) estimation method is one of the traditional methods use to estimate the distance between the transmitter and receiver based on the time delay between transmission and reception [92]. Time-of-Arrival (ToA) estimation is a range-based technique that uses the time it takes for a signal to travel between nodes to determine distances, which are then used to calculate the location of the sensor nodes [97]. ToA localization works by measuring the time it takes for a signal to travel from a known location (anchor node) to an unknown location (sensor node). Knowing the speed of the signal (e.g., radio waves), the distance between the nodes can be calculated. By obtaining the ToA from multiple anchor nodes, the sensor node's position can be calculated using techniques like trilateration (3D) or triangulation (2D). It means that a combination of this method with trilateration or angulation is used to find the position of the target or rather unknown node in a network topology [98], [99].

Consider two nodes exchanging a single message containing a global transmission time-stamp, where the receiving node must be able to determine the global reception time-stamp precisely. The clocks at both nodes (anchor and target) must be precisely synchronized and maintain global time. This is to avoid challenges such as clock offsets, drifts and jitters resulting from clock errors as small timing error will amount to large distance error reading. The Time Difference, ΔT in transmission Tt to reception Tr is used to calculate the distance between the anchor node and target. This is expressed mathematically below;

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$$\Delta T = K(\frac{d}{c}) \quad (2)$$

Where; ΔT is the Time Difference between the anchor node and target, K is a constant that depends on the transmission device parameter (K = 1 under perfect condition), d is the distance between the anchor and target while c whose value (c ≈ 3 × 10^8 m/s) is the speed of light in free space. We are going to discuss the three types of TOA ranging techniques here, purposely used to tackle the issue emanated from clock synchronization namely; One-Way TOA, Two-Way TOA and Differential Two-Way TOA.

- **One-Way Time of Arrival (O-WTOA):** The One-Way TOA is the simplest form of TOA ranging techniques where it's required that the clocks of both nodes are synchronized and maintain a global time as shown in Figure 5 below. Adhering to this condition above, the sending node (A) simply sends a packet containing the transmission time (τ_1), the receiving node know as target (T) records the reception time of the packet (τ_2). The time of arrival;

$$\Delta\tau = \tau_2 - \tau_1 \quad (3)$$

This is simply the time difference of the signal at A and T. The time of flight is then calculated using Equation (3) above. However, in this technique, it's difficult to achieve accuracy in distance estimation due to the effect of synchronization error which could be very devastating for a slight offset of 1 sec leads to 30 km of distance disparity.

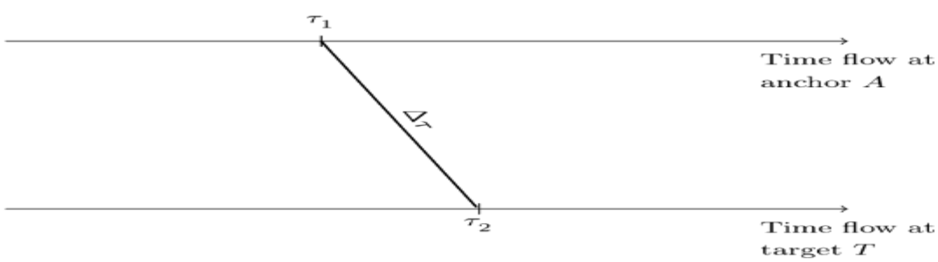

Figure 5: One-Way Time of Arrival (O-WTOA) [100]

- **Two-Way Time of Arrival (T-WTOA):** One way to compensate for different time offsets is by sending two messages. From Figure 6 below, the node (T) known as the target node can determine its distance from another node (A). It initiates the measurement by sending an initial message to node (A), we then estimate the time of arrival;

$$\Delta\tau = \{\frac{(\tau 4 - \tau 1) - \tau 1}{2}\} \quad (4)$$

and the round trip;

$$\tau_{RT} = 2\Delta\tau + \tau_T \quad (5)$$

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The effects of synchronization errors such as clock offsets were resolved but still the measured distance is affected by clock drift between the anchor node (A) and Target (T), arbitrary time delay τ_T and clock jitters still pose danger in the accuracy of the estimated distance.

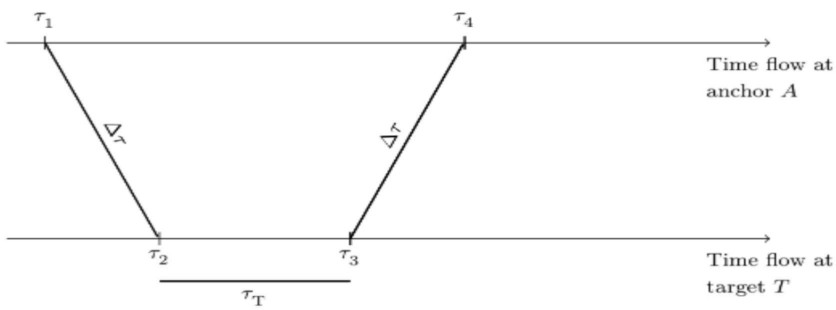

Figure 6: Two-Way Time of Arrival (T-WTOA) [100]

- **Differential Two-Way Time of Arrival (DT-WTOA):** In the procedure, as shown in Figure 7 below, the Two-Way ranging technique as explained above but with a double packet exchange between anchor node (A) and target (T) using a time-delay of τ_T and $2\tau_T$ at target node (T). Hence, the time of arrival is;

$$\underline{\Delta}\tau = \tau_4 - \tau_1 - \frac{(\tau'4-\tau'1)}{2} \qquad (6)$$

Finally, the effect of clock drift and arbitrary time delay were drastically reduced to a negligible value, still yet clock jitters pose a serious danger to distance estimation.

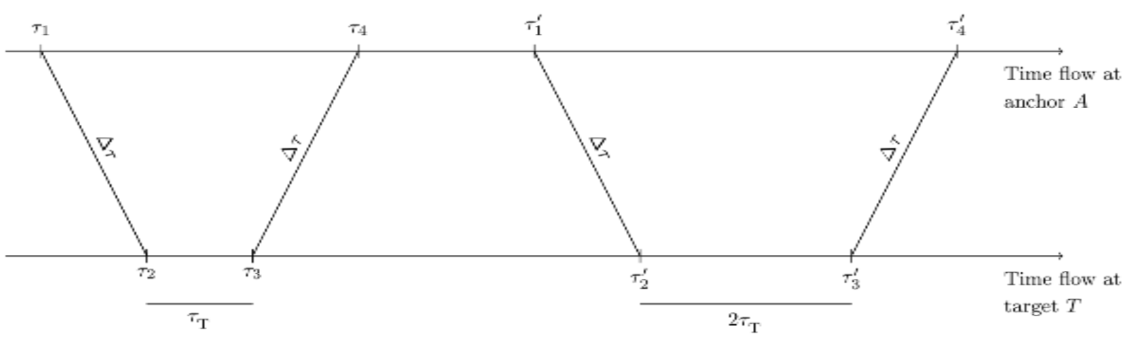

Figure 7: Differential Two-Way Time of Arrival (DT-WTOA) [100]

In general, TOA is affected by clock synchronization, multipath effects and Non-Line of Sight (NLOS), however, these can be solved by clock synchronization algorithms, multipath mitigation techniques and NLOS compensation algorithms.

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7.3. Time Difference of Arrival (TDOA)

TDOA localization estimates the location of a target (e.g., a sensor node) by measuring the time difference between when a signal from that target arrives at different receiver nodes (or anchor nodes) [101]. This technique measures the different in arrival time of a signal from unknown node (T) and multiple anchor nodes (for instance; 1, 2 & 3) as shown in Figure 8 below. It relies strongly on the quality of reception and a precise synchronization is critical for higher accuracy distance estimation to be obtain [102]. We calculate the various intervals between the various anchor nodes (1, 2 & 3) and the unknown node (Target node, T) by observing the difference in the time of arrival of the transmitting signals from the unknown node, T to the three anchor nodes (1, 2 & 3). The accuracy of this technique is affected by a multipath, NLOS and synchronization error but can be improved by increasing the distance between the anchor nodes with respect to unknow node, since this will improve the difference between arrival times.

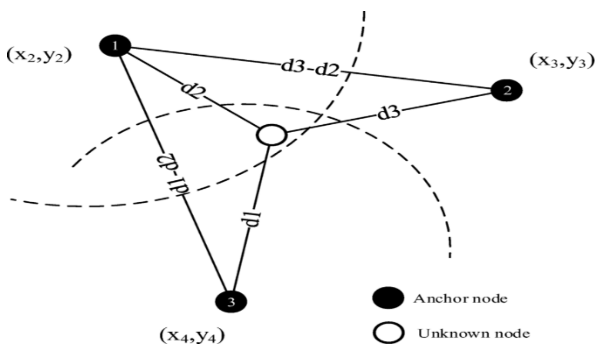

Figure 8: Time Difference of Arrival (TDOA) [103]

We use Equation (7) to calculate the TDOA between the anchors and target as;

$$\text{TDOA} = (A_{it}-T_t) = \Delta_t = (d_i-d_r)/c \quad (7)$$

Where; Δ_t is the time differences of arrival between the anchor nodes and the unknown node, d_i-d_r are the distances from the anchor nodes to the unknown node and c is the speed of light in free space. The issue of clock synchronization is not needed at the transmitter but it's required at the receiving end to minimize the errors of synchronization. This technique is robust to multipath and has a high accuracy ratio than TOA technique, however it has cost implications as it requires multiple receivers and complexity in calculations. In order to mitigate these challenges, the following algorithms can be used to improve the accuracy of the system; Kalman Filter, Non-Linear Least Square and Linear regression

7.4. Phase Difference of Arrival (PDOA)

Phase Difference of Arrival (PDOA) localization is a range-based technique that leverages the phase difference of a signal received at multiple antennas to determine the position of a target node [104]. The introduction of the Radio Frequency Identification gave birth to the popularity of this technique. This technique has permitted consistent and intelligent signal processing for accurate distance estimation. It measures the phase difference of a signal arriving at multiple antennas or receivers, which is related to the angle of arrival (AoA) of the signal. PDOA relies on the relationship between the phase difference and the distance (or angle) between the target node and the receiver, making it a range-based technique. PDOA based ranging takes the concept of Continuous Wave (CW) dual frequency technique employed in radar systems [105]. In this technique, a continuous wave signal is transmitted and received through an active receptor at a particular frequency, f_n. Take for instance, if it is operated at two frequencies f_1 and f_2, the observed phase difference ($\boldsymbol{\varphi}_2$-$\boldsymbol{\varphi}_1$) of the CW signal at these two frequencies is used to estimate the distance between the transmitter anchor node (A) and active reflector node target (T) as;

$$d = \frac{c\Delta\varphi}{4\pi f} = \frac{c(\varphi 2-\varphi 1)}{4\pi f(f2-f1)} \quad (8)$$

The PDOA ranging technique is a much more improved ranging procedure in terms of accuracy and robustness as compared to RSS-based, TOA-based and TDOA-based ranging techniques [106]. PDOA can be more accurate than other range-based techniques, especially in indoor environments or when dealing with multipath signals. This technique mitigated the effect of synchronization errors, additional hardware and NLOS conditions due to multipath propagations. Painful enough, due to the dual-frequency scheme, the maximum possible distance that can be measured using this technique in overall is estimated to be short and is expressed as, $d_{min} = \frac{c}{2\pi fmin}$. PDOA is used in various applications, including indoor positioning, tracking, and RFID.

7.5. Angle of Arrival (AOA)

Angle of Arrival is a localization method used for estimation of the location of a target node by measuring the angle of arrival of signals from multiple anchor nodes or rather called reference points [107]. Angle-based estimation is suitable for applications requiring high accuracy and robustness, particularly in scenarios with limited range [108]. In a WSN, anchor nodes (nodes with known locations) transmit signals. A node to be localized measures the AoA of these signals from the anchor nodes. AoA estimation can be achieved using antenna arrays or by determining the direction of propagation of a radio-frequency wave. The technique used here are; Angle of Arrival (AOA), Direction of Arrival (DOA) and Bearing Estimation (BE) [109], [110]. In this strategy, the first is that the receiver uses the antenna amplitude response and the second, the receiver uses the antenna phase response.

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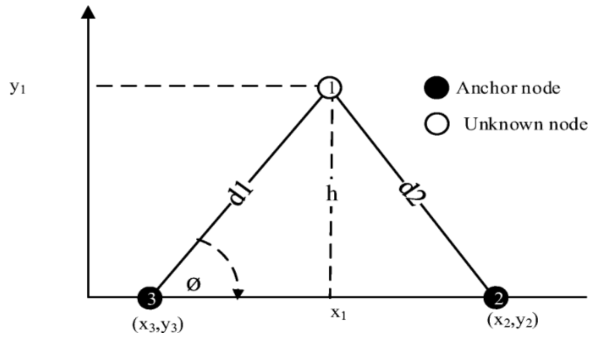

Figure 9: Angle of Arrival (AOA) [111]

The principle behind AOA is that it uses the angle of incidence of the signal at the receiver to determine the location of the transmitter. The mathematical representation of AOA is given below:

$$\theta = \arctan(\Delta y/\Delta x) \quad (9)$$

where θ is the angle of arrival, Δy is the difference in y-coordinates, and Δx is the difference in x-coordinates. We have types of AOA which are briefly explained below: (1). Single-Path AOA: This uses a single antenna element to measure the angle of arrival. (2). Multi-Path AOA: This uses multiple antenna elements to measure the angle of arrival. (3). Differential AOA: This measures the difference in angle of arrival between two or more receivers.

8. Hybrid Localization Techniques

To mitigate the limitations of individual localization methods, hybrid localization techniques have been developed. These techniques combine multiple methods to improve accuracy, robustness, and efficiency [112]. Hybrid methods may combine range-based and range-free techniques or fuse different types of range-based measurements. Hybrid localization techniques combine multiple ranging methods (like RSSI, TDOA, TOA) to improve accuracy and robustness compared to relying on a single technique, addressing challenges like multipath effects and varying environmental conditions. Relying on a single localization technique (e.g., RSSI) can lead to inaccuracies due to factors like signal attenuation, multipath propagation, and environmental interference. By combining different ranging methods, hybrid techniques can leverage the strengths of each, mitigating their individual weaknesses and resulting in more accurate and reliable localization. Hybrid approaches can be designed to be cost-effective, using readily available hardware and software components [113]. Hybrid examples are:

- **TDOA/TOA & RSSI Hybrid**: Here the RSSI measures the strength of the received signal, providing a rough estimate of distance. While, TDOA/TOA measures the time difference or time of arrival of signals from different nodes, enabling more precise distance calculations. Combining time-based and strength-based distance measurements can help overcome the limitations of each method. TDOA/TOA can be more accurate in line-of-sight conditions, while RSSI is less affected by synchronization errors. Combining RSSI for initial localization and TDOA/TOA for refined positioning, addressing the limitations of each method.

- **AOA & RSSI Hybrid:** The AOA determines the direction of the incoming signal, providing information about the node's relative position. Combining RSSI for distance estimation and AOA for direction finding, improving localization accuracy.

Table 2 below equally shows in clarity the strength and weakness of the four major range-based localization techniques in WSNs. In other to achieve a certain objective, Network Engineers should pay attention in choosing the techniques that best suits their purposes.

Table 2 Comparison of the four major Range-base Localization Techniques

	Function	RSSI	TOA	TDOA	AOA
1	Algorithm type	Signal strength-based	Time-based	Time difference-based	Angle-based
2	Algorithm complexity	Low; Uses signal strength measurements to estimate location	Medium; Requires precise timing synchronization and calculation of signal travel time	High; Requires calculation of time differences between the signals received at different nodes	Very high; Requires complex signal processing and antenna array configuration
3	Classification in terms of measurement type	Uses signal strength patterns	Uses time measurements	Uses time measurements	Uses angle measurements
4	Accuracy	Low	High	High	Very high
5	Overhead	Low	High	Medium	Very high
6	Hardware requirements	Low	Medium	Medium	High
7	Synchronization requirements	Low	High	Medium	Low
8	Communication requirements	Low	Medium	Medium	Low
9	Computational Cost	Low	Medium	High	Very high
10	Computational requirements	Low	Medium	High	Very high
11	Processing	Low	Medium	High	Very high

	requirements				
12	Data requirements	Low	Medium	Medium	Very high
13	Scalability	Medium	High	Very high	Average
14	Implementation	Easy	Moderate	Moderate	Complex
15	Software complexity	Low	Medium	High	Very high
16	Integration requirements	Easy	Medium	Medim	Complex
17	Suitability	Outdoor application	Outdoor application	Indoor application	Outdoor application
18	Location estimation method	Trilateration or fingerprinting	Trilateration	Hyperbolic positioning	Triangulation

9. Other types of localization

Beyond the broad categories of range-based and range-free, WSN localization can be further classified by other characteristics such as GPS-Based vs. GPS-Free, Anchor-Based vs. Anchor-Free, Centralized vs. Distributed, and Fine-Grained vs. Coarse-Grained localization. Each of these classifications describes different aspects of how a network locates its sensor nodes, focusing on the presence of known-position nodes, where computation happens, the use of external positioning systems, and the precision of the location estimates.

9.1. GPS-Based VS GPS-Free Localization

WSN localization techniques are used to measure the locations of the sensors which are deployed in different places. The location of the sensors can be determined using a Global Positioning System (GPS). GPS works in node location by using a network of satellites orbiting the Earth to provide location information to GPS receivers on the ground. GPS provides location information to sensors, enabling them to determine their position, orientation, and track movement [8]. GPS-Based Sensor Localization perform a task in the following module; Module 1, GPS Receiver: Integrated into the sensor node or device. Module 2, Signal Reception: GPS receiver detects signals from multiple infrastructures. Module 3, Location Calculation: GPS receiver calculates its location (latitude, longitude and altitude) using trilateration or multilateration. The GPS-free category refers to localization schemes that do not depend on any external positioning systems like GPS, using only the network's internal connectivity and signals to determine node positions.

9.2. Anchor-Based vs. Anchor-Free

Anchor-based WSN localization uses fixed, pre-positioned nodes with known locations (anchors) to determine the positions of unknown nodes. This method uses a set of "anchor" nodes whose coordinates are known, often through GPS, whereas anchor-free localization relies on relative node positions and network topology without requiring any fixed points, though it often involves clustering or other geometric techniques. This approach determines node positions without any pre-established, globally known anchor nodes. Anchor-based methods offer global positioning but require pre-deployment of anchors, while anchor-free methods provide local, relative coordinates but can offer more flexibility and robustness in dynamic environments[114]. In Anchor-based, the unknown nodes communicate with these anchors and use the information (like distance or signal strength) to estimate their own positions through various geometric techniques like trilateration or multilateration. However, in Anchor-free, instead of global anchors, it often involves techniques like clustering nodes and having gateway nodes within each cluster create local maps, or using relative distance/topological information between unknown nodes to establish their relative positions.

9.3.Centralized vs. Distributed localization

Centralized systems concentrate control and resources in a single point, offering easier management and a clear chain of command but risking single points of failure and bottlenecks. Distributed systems spread control and resources across multiple connected nodes, providing scalability, fault tolerance, and enhanced performance, but requiring complex coordination and potentially increasing maintenance costs. The choice between centralized and distributed depends on the specific application's needs for efficiency, resilience, and scalability [115]. Centralized systems easier to oversee and implement changes, provides a well-defined chain of command, may be less expensive to maintain due to fewer components, facilitates a unified goal and vision for the organization or system. Whereas, distributed systems, the system's longevity is more certain, workloads can be divided, leading to higher overall performance, the system can continue to function even if some nodes fail, can handle large-scale, dynamic applications and high transaction volumes.

9.4.Fine-Grained vs. Coarse-Grained localization

Fine-grained localization provides precise location data by using detailed measurements like signal waveforms or precise timing, while coarse-grained localization offers broad, approximate location information by relying on minimal data, such as binary proximity or broad direction. Fine-grained localization is more complex and resource-intensive but yields higher accuracy, whereas coarse-grained methods are simpler to implement with lower costs and resource demands but offer lower precision[116], [117]. Fine-grained offers lower accuracy, providing a broader area or more general position, requires less processing power and equipment, simpler to implement and manage, relies on minimal, discrete information, such as binary near/far data, general directions (like cardinal directions), or the presence of a few general regions. Whereas, Coarse-grained provides high accuracy, allowing for more precise tracking of movement or position, demands higher computational resources and more complex equipment, more complex to implement and configure, employs detailed, real-valued, or highly quantized discrete measurements, such as precise radio signal strength, precise timing information, or detailed angular data.

9.5. Indoor Localization

Indoor localization techniques use fixed stations for discovering the location of sensor nodes. Fixed stations are placed in the area where the location discovery is required. Nodes communicate with each other and/or central node. In other words, it is the ability to determine the position, orientation, and track the movement of nodes or devices within a building or enclosed space [118]. Indoor localization (e.g. Wi-Fi, Bluetooth, Zigbee, IEEE 802.15.4 and Ultra-Wideband) encounters so many challenges such as; (1) GPS signals are weak or unavailable indoors. (2) Multipath interference from walls, floors, and ceilings. (3) Limited visibility and line-of-sight issues. (4) Dynamic environment (moving people, furniture, etc.). (5) Node mobility and dynamics. (6) Scalability and cost considerations. (6) Energy efficiency and power consumptions. Indoor localization is applicable in Smart Homes and Buildings, Industrial Automation and Control, Healthcare (patient tracking, asset management), Retail (customer tracking, personalized marketing), Emergency Response and Evacuation, Asset Tracking and Management, Inventory Management, etc [70].

9.6. Sensor Network Localization

Sensor network localization is the process of determining the physical locations of sensor nodes within a wireless sensor network (WSN) using various techniques, often without relying on GPS or manual configuration [24]. This localization method does not depend on the presence of fixed stations. Each sensor node estimates its location by acting itself as beacon node. The location of a sensor node can be determined using GPS and send this information to every other node in a network. The time difference the receptions of beacon signals from different nodes is used to determine the location [119]. Some localization techniques require the location of beacon nodes. These techniques are called Multi-Lateration (ML) techniques. Some ML techniques are as follows; Atomic ML, Iterative ML and Collaborative ML.

9.7. Absolute localization

Absolute localization determines a node's precise position (latitude, longitude, and altitude) directly, without relying on a reference point or prior location, using techniques like satellite navigation or visual matching to a georeferenced map [120]. Absolute localization aims to determine the exact location of a node or object in a global coordinate system, providing a precise position independent of any initial or relative location. Absolute localization refers to determining the precise location of sensor nodes within a known reference frame or coordinate system. In absolute localization, the global coordinates (e.g., x, y, z) is used to determine the absolute positioning of a target node not relative to other nodes. It has a very high accuracy (~1-10 cm). There is no ambiguity or uncertainty and it is free from drift or accumulated errors. Absolute localization is a real-time localization and one of the GPS-based localization which requires that the sensor nodes must be equipped with GPS receiver [121]. In absolute localization method, the sensor nodes equipped with GPS receiver are used as reference nodes. There are three methods Absolute Localization are used in locating the precise location of an objects namely:

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- **Satellite Navigation:** Systems like GPS use signals from satellites to calculate distances and determine position based on triangulation or trilateration.
- **Visual Localization:** This approach uses visual features in the environment, often compared to a pre-existing map or imagery, to determine position.
- **Landmark Matching:** Identifying and matching distinct features in the environment with a known map to determine position.

9.8. Relative localization

Relative localization is a technique used to determine the position of a target node in a network, but instead of finding their absolute location in a global coordinate system, it focuses on their positions relative to other nodes within the network [122]. Relative localization focuses on determining the position of a senor node relative to each other, rather than absolute coordinates, by using measurements between them without relying on external information. Relative localization determines the position of a target node relative to other beacon nodes or reference points, rather than absolute coordinates. Instead of relying on external information like GPS or pre-defined landmarks, relative localization uses measurements (like distance or angle) between the nodes to estimate their relative positions [123]. Here the relative positioning e.g., node A is 5 or 10m away from node B. There are no global coordinates (e.g., x, y, z). It is associated with lower accuracy due to drift and it is purely infrastructure-based (e.g., anchor nodes). The indirect approach of localization is termed as relative localization. Since the location of sensor nodes can be determined based on the relative position of the other sensor nodes, this localization method is called an indirect approach. It can be a more cost-effective solution than absolute localization, as it does not require expensive external infrastructure.

9.9. Triangulation

Triangulation is a localization technique that uses the distances from a target node to multiple anchor nodes (known locations) to determine the target's position. It is an estimation method used in determining the location of a target node using the angles and distances from multiple reference node or beacon nodes, using the trigonometric laws, law of sines and cosines are utilized to obtain the target node location [126]. WSNs often require knowing the location of sensor nodes for various applications, such as environmental monitoring, tracking, and data collection. The core idea is to form triangles using the target node and anchor nodes. By measuring the distances (or angles) between the target and the anchor nodes, the target's position can be calculated using geometric principles. The measured distances (or angles) are used to solve a system of equations that determine the target node's coordinates. Triangulation is categorized into; Angle-Based Triangulation (ABT): Used for the determination of the location of target node using angle measurements from multiple anchor nodes, Distance-Based Triangulation (DBT): Used for the determination of the location of target node using distance measurement from multiple anchor nodes and Hybrid-Based Triangulation (HBT): This is a combination of ABT and DBT to robustness and accuracy [127]. It has overwhelming advantages such as; high accuracy, robust to multipath effects and easy implementation, however, its demerits are; very limited range, sensitivity to anchor placement and multiple anchor requirement. The accuracy of triangulation depends on the number and distribution of anchor nodes, the accuracy of distance measurements, and the geometry of the triangles formed.

Triangulation is equally a real-time localization technique used to determine the position of a node using the intersection of multiple lines or curves. Triangulation are of three types namely: (1) Lateration Triangulation (time-of-arrival), (2) Angulation Triangulation (angle-of-arrival) and (3) Hybrid Triangulation (combines lateration and angulation). Triangulation of three reference points is termed Trilateral Triangulation (three reference points), while more than three reference points is termed, Multilateral Triangulation (more than three reference points), while Iterative Triangulation (refines estimate through iterations).

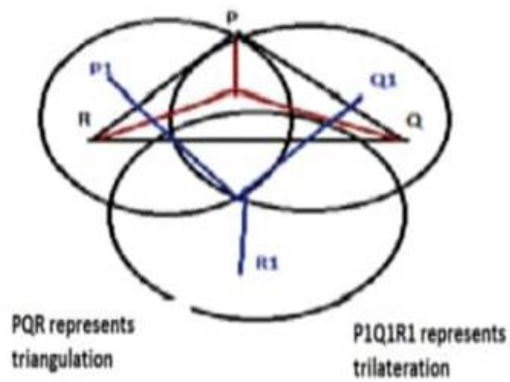

Figure 10: Triangulation and Trilateration in WSN [128]

Triangulation is a widely used approach in wireless sensor network for computing position of sensor nodes. This method uses information regarding angles. It is similar to trilateration. It has its own challenges such as: precise reference point locations, computational complexity, sensitivity to geometry and layout.

9.10. Trilateration

Trilateration is a geometric technique used to determine the location of a sensor node by measuring its distances from at least three known anchor nodes (or reference locations) [132]. It is a subsidiary of lateration. Trilateration, similar to GPS, relies on measuring the distances between an unknown node (sensor node) and three or more points with known locations (anchor nodes) to pinpoint the unknown sensor node's position. It is used to estimate the location of a target node using distance measurements from three or more reference anchor nodes or beacon nodes [133], [134]. The distance measurements are typically obtained using techniques like Received Signal Strength Indicator (RSSI) or Time of Arrival (TOA). These distances are used to create a set of equations, and solving these equations yields the coordinates of the unknown sensor node. The intersection of the spheres (or circles in 2D) centered at the anchor nodes, with radii equal to the measured distances, determines the location of the sensor node. The

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intersection point of the three circles is figured, which gives a solitary point which is a location of the unlocalized sensor node [114], [135]. Trilateration provides a relatively simple and computationally efficient method for determining sensor node locations. Assume we have three anchor nodes as shown in Figure 10, P1, Q1, and R1, with known locations (xP1, yP1), (xQ1, yQ1), and (xR1, yR1) respectively. We want to find the location of target sensor node U at (x, y). Firstly, we measure the distances between U1 and P1(r1), U1 and Q1(r2), and U and R1(r3). We can then use the following equations to find the location of U1:

- $(x - xP1)^2 + (y - yP1)^2 = r1^2$ (9)
- $(x - xQ1)^2 + (y - yQ1)^2 = r2^2$ (10)
- $(x - xR1)^2 + (y - yR1)^2 = r3^2$ (11)

Solving these equations will give you the coordinates (x, y) of the sensor node U1.

9.11. Multilateration

Multilateration is a localization technique that estimates the location of a node by measuring its distances to multiple known anchor nodes (or beacons) and then determining the point that minimizes the sum of squared distances to those anchors [136]. It is still a subsidiary of lateration. Multilateration is a range-based localization technique that relies on distance measurements between the sensor node and a set of anchor nodes with known locations [137]. Equally, the sensor node measures its distance to the anchor nodes, which can be done using techniques like Time of Arrival (TOA), Time Difference of Arrival (TDOA), or Received Signal Strength (RSS). The sensor node's location is estimated by finding the point that minimizes the sum of squared distances to the anchor nodes, based on the measured distances. Multilateration can be formulated as a non-linear optimization problem, where the objective is to find the location of the sensor node that best fits the measured distances to the anchor nodes. One of the limitations of classical multilateration is that it assumes that the anchor locations are error-free, which is not always the case in real-world scenarios [138]. We have two types of multilateration; 2D and 3D multilateration. In 2D multilateration, the location of a target node in a two-dimensional space is achieved using distance measurement from four or more reference anchor or beacon nodes. While that of 3D Multilateration, it is the location of a target node in a three-dimensional space from four or more reference anchor or beacon nodes. Figure 11, depicts the three major geometric techniques in position-based estimation.

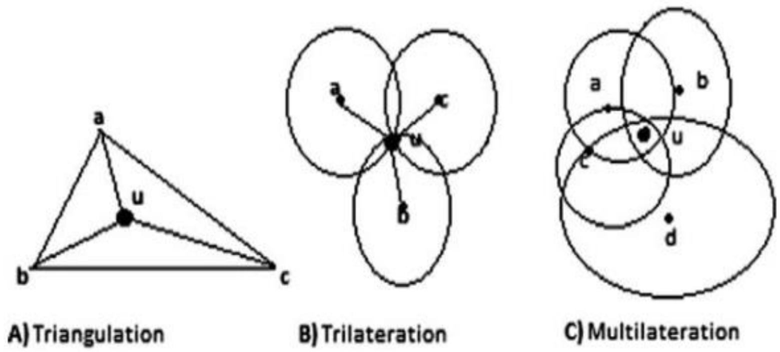

Figure 11: Geometric techniques in Position-Based Estimation [137]

10. Smart Cities and WSN Localization

Localization in smart cities plays a key role in enhancing the quality of life for residents and improving the efficiency of urban infrastructure [154] [155]. Wireless Sensor Network (WSN) localization is crucial for enabling efficient monitoring, resource management, and informed decision-making by providing real-time location data of sensors and objects, enhancing situational awareness and optimizing various urban services [156].

10.1. Importance and application in Smart City

In these applications, precise and reliable localization is required to ensure the effective deployment of services and data collection. The important and application of WSN localization in a smart city is grouped into four (4) categories for better guideline namely:

A. Enhanced Situational Awareness:

- Real-time Monitoring: WSN localization enables real-time tracking of sensor nodes and objects, providing valuable insights into the current state of the city.
- Precise Location Data: Localization algorithms help determine the precise location of sensors, which is essential for accurate data collection and analysis.
- Improved Decision-Making: By knowing the location of sensors and objects, city managers can make informed decisions about resource allocation, emergency response, and infrastructure management**.**

B. Optimized Resource Management:

- Efficient Waste Management: Localization can help optimize garbage truck routes and ensure efficient waste collection, reducing costs and improving environmental sustainability.
- Water and Energy Management: Efficient monitoring and control of energy usage, including localization of devices and nodes in smart grids. Localization can help monitor water and energy consumption and identify leaks or inefficiencies, leading to better resource management.

- Management: Tracking the location of assets such as public transportation vehicles, waste bins, and delivery drones.

C. Enhanced Security and Safety:

- Emergency Response: Localization can help emergency responders locate individuals in distress or identify the source of an emergency, leading to faster and more effective responses.
- Environmental Monitoring: Localization can help monitor air and water quality, identify pollution sources, and track hazardous materials, enhancing public safety.
- Security Surveillance: Localization can be used to track the movement of people and vehicles, enhancing security and preventing crime.
- Smart Healthcare: Real-time tracking of medical assets, emergency services, and patient health monitoring.
- Emergency Services: Localization of emergency responders (firefighters, paramedics, etc.) for quicker deployment during incidents.

D. **Improved Urban Planning and Development:**

- Data-Driven Decision-Making: Localization provides valuable data for urban planning and development, allowing city planners to make informed decisions about infrastructure, transportation, and land use.
- Smart Infrastructure: Localization can help optimize the design and deployment of smart infrastructure, such as smart streetlights, parking sensors, and public transportation systems.
- Citizen Engagement: Localization can enable citizens to participate in smart city initiatives by providing them with real-time information about traffic, pollution, and other relevant issues.
- Intelligent Transportation Systems (ITS): Accurate vehicle and pedestrian localization enable real-time intelligent traffic management, accident detection, and vehicle tracking, reducing congestion, improve safety and optimizing traffic flow.
- Urban Planning and Infrastructure Monitoring: Continuous monitoring of buildings, bridges, and other infrastructure for maintenance, with localized sensing to detect stress or damage.

10.2. Challenges of Localization in Smart Cities

Despite the potential, localization in WSNs within smart cities faces several challenges:

- **Environmental Factors**: Urban environments are complex, with physical obstacles, multipath propagation, and interference that affect signal strength and reliability.
- **Node Density**: High node density in smart cities may lead to interference, congestion, and energy constraints, affecting localization accuracy.
- **Non-line-of-Sight (NLOS) Issues**: In dense urban environments, line-of-sight between nodes is often obstructed, leading to measurement errors in distance-based techniques like TDOA and RSSI.

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- **Energy Constraints**: Many WSN nodes in smart cities are battery-powered, and localization techniques that rely on frequent communication or complex computations may not be energy-efficient.
- **Accuracy and Reliability:** Localization algorithms must be accurate and reliable to provide meaningful data.
- **Scalability:** Localization systems must be able to handle a large number of sensor nodes and objects.
- **Security and Privacy:** Localization data must be protected from unauthorized access and misuse.

11. Comparative Analysis

The pros and cons of different algorithms in the localization process were discussed as shown in Table 1 and 2. At the input stage of localization process, a hybrid approach of multiple sensors stands outstanding. The same goes to distance estimation, a combination of any of these; RSS, TOA, TDOA and AOA will outperform individual techniques. In position estimation, Machine Learning-based Fingerprinting techniques outperforms any of these techniques; Trilateration, Triangulation, Multilateration, Fingerprinting. In Localization Algorithm, Adaptive and hybrid approaches will outperform any of these techniques; Kalman Filter, Particle Filter, EKF, UKF in refining the network, interestingly, using Ultra-Wideband (UWB) technology has led to high-precision localization. However, every localization schemes are geared towards achieving a distinctive need. Progressively the quantity of anchor node and using the best techniques in deployment minimizes the error of the localization thereby improving the reliability, efficiency and accuracy of the network.

12. Conclusion

This paper gives a broad review of localization process, their methodologies in each stage of the networks design. The classification of localization was discussed and references were made to authors who have contributed immensely in each class of localization. In order to achieve scalability, robustness, accuracy and energy efficiency, researchers have focused on these interesting areas which were reviewed; Indoor Localization, Machine Learning/Artificial Intelligence (AI) for Localization, Internet of Things (IoT) Localization, Autonomous Systems Localization, 5G-based Localization, Localization in Harsh Environments, Multi-Modal Fusion, Edge Computing for Localization: Processing localization data at the edge for reduced latency and improved accuracy.

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