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Review article

Advances on localization techniques for wireless sensor networks: A survey

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ABSTRACT

Localization in wireless sensor networks (WSNs) is regarded as an emerging technology for numerous cyber-physical system applications, which equips wireless sensors with the capability to report data that is geographically meaningful for location based services and applications. However, due to the increasingly pervasive existence of smart sensors in WSN, a single localization technique that affects the overall performance is not sufficient for all applications. Thus, there have been many significant advances on localization techniques in WSNs in the past few years. The main goal in this paper is to present the state-of-the-art research results and approaches proposed for localization in WSNs. Specifically, we present the recent advances on localization techniques in WSNs by considering a wide variety of factors and categorizing them in terms of data processing (centralized vs. distributed), transmission range (range free vs. range based), mobility (static vs. mobile), operating environments (indoor vs. outdoor), node density (sparse vs. dense), routing, algorithms, etc. The recent localization techniques in WSNs are also summarized in the form of tables. With this paper, readers can have a more thorough understanding of localization in sensor networks, as well as research trends and future research directions in this area.

1. Introduction

Localization in wireless sensor networks (WSNs) is one of the central components of a variety of emerging applications including cyber-physical systems, military [1,2], eHealth [3–6], environment monitoring [7], home and office automation [8,9], weather forecasting [10] and so on. Many of these applications need location based services. Although GPS is a direct solution to the localization problem, the high cost, high power consumption, and poor performance of GPS inside an indoor environment have necessitated the research on localization algorithms [11]. Over the past few years, the scientific world has observed a lot of research efforts on this topic. Note that the localization is defined as the determination of the position of an unknown node, sometimes with the help of nodes with known position, and at other times using the connectivity information between the unknown nodes. Recent studies have investigated the effect of mobility in localization [12–14], real world applications [15–17], “Anchor Based” and “Anchor Free” localization methods [18], “Range Based” localization algorithm (distance measurement technique to calculate the location of unknown nodes) and “Range Free” localization algorithm (connectivity rather than distance) [19], “Cooperative” (communication exists among all nodes) and “Non-Cooperative” (unknown nodes communicate only with the anchor nodes) algorithms [20], “Centralized” algorithm based localization (*aka* network-centric positioning [21]) and “Distributed” algorithm (no central control on the determination of the node’s position and each node estimates its location based on the locally gathered information - *aka* “self-positioning” algorithm [21]) [22].

In this paper, localization techniques/algorithms in WSN are divided into “Sparse vs. Dense”, “Anchor based vs. Anchor free”, “Indoor vs. Outdoor”, “Cooperative vs. Non-Cooperative” and “Static vs. Mobile” categories as shown in Fig. 1. Furthermore “Anchor Based” and “Anchor Free” localization algorithms are further classified into “Range Based” and “Range Free” algorithms. The above classification is made considering the network size (sparse vs dense) and specific application of certain type of algorithms (indoor). Furthermore, they are classified based on their mobility (static vs mobile) and usage of anchor nodes (anchor based vs anchor free). Also, at the end of anchor based and anchor free localization algorithm sections, comparison tables are included to

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Table 1
Comparison among surveys involving localization in WSNs.

Survey works	Focus	Static coverage	Mobility coverage	Remarks
[Mao 2006] [23]	Localization	Extensive	No	Extensive details about static localization schemes
[Mao 2007] [24]	Localization	Extensive	No	Extensive details about static localization schemes
[Amundson 2009] [25]	Localization	No	Not extensive	Details on MWSNs with limited algoritumic details
[Faheem 2009] [26]	Data dissemination	Yes	Specific/Extensive	Details on data dissemination strategies of mobile sink
[Mao 2009] [27]	Localization	Extensive	No	Extensive details about static localization schemes
[Pal 2010] [28]	Localization	Extensive	No	Static localization is classified into many classes
[Dong 2013] [29]	MAC protocol	Extensive	Extensive	Comprehensive and comparative study of MAC
[Han 2013] [30]	Localization	Extensive	Extensive	Localization is classified based on mobility of the nodes
[Mesmoudi 2013] [31]	Localization	Extensive	Limited	Nice details of the algorithms with distinctive classification
[Tunca 2014] [32]	Sink routing	Extensive	Extensive	Detailed study of recent proposals on mobile sink routing
[Gu 2014] [33]	Sink mobility	Extensive	Extensive	Development flow of sink mobility management
Our work	Localization with all factors	Extensive	Extensive	Discusses algorithms from a new point of view

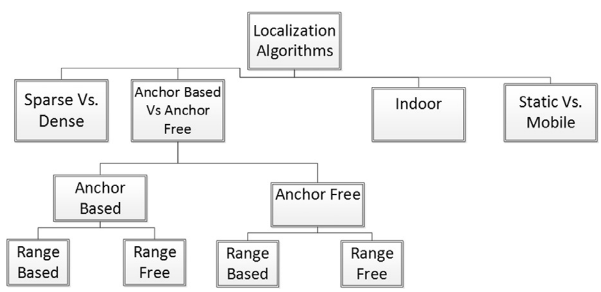


Fig. 1. A typical classification of localization techniques in WSNs.

characterize each algorithm based on different factors such as whether they are centralized or distributed and whether they are cooperative or non-cooperative. Thus any reader who wants to find a specific algorithm that needs to fulfill some special requirements can use this vast classification will help him to find recently proposed algorithms that suit the demands.

Although there are survey papers that provide information about the localization in WSNs, more up to date activities of rapidly advancing research area is to be brought to the research community. Furthermore, state-of-the-art literature does not provide recent advances on localization in WSNs by categorizing them in terms of their types and a wide variety of factors, nor does it categorize them in terms of data processing (centralized vs. distributed), transmission range (range free vs. range based), mobility (static vs. mobile), operating environments (indoor vs. outdoor), cooperative vs non-cooperative, node density (sparse vs dense), routing, algorithms, etc. Furthermore, we have compared survey papers that are already published in the literature with our work as given in Table 1.

Mao et al. have presented a comprehensive survey on static localization in WSNs in [24,27] considering different factors such as centralized and distributed, single hop, and multiple hop. This survey is relatively older and did not consider mobility issues of the sensor networks. Furthermore, these lack recent works in this field as well as discussion on open issues and research challenges. Amundson et al. have surveyed localization algorithms for mobile wireless sensor networks (MWSN) in [25]. This paper includes MWSN architecture, advantages of mobility, differences between WSNs and MWSNs, localization steps in MWSNs, and effect of mobility on localization. While this paper covers a lot of issues regarding MWSNs, it lacks the detailed description of specific algorithms and their comparative study. Faheem et al. have presented a survey on data dissemination of mobile sink in [26] by classifying the data dissemination techniques based on application type, mobility pattern, number of sinks, and route creating entities. However, this work is also relatively older and lacks recent research ideas, and our work differs from their work since their survey does not provide any discussion on localization in wireless sensor networks. Pal has summarized some proposed localization algorithms in [28] under two classifications: centralized and distributed. Dong et al. in [29] have surveyed mobility related issues and mobility-aware medium access control (MAC) protocol in WSNs. This survey discusses different mobility patterns and models, state-of-art mobility estimation methods, and comprehensive and comparative investigation of proposed mobility-aware MAC protocols. This survey has discussed only the mobility issues and MAC protocols of WSN rather than localization in WSNs. A survey on localization in WSNs is presented by Han et al. in [30] by considering algorithms based on static and mobile nodes as well as on range based and range free. Although this is an excellent summary of recently proposed localization algorithms, it was published in 2013 and does not include the research published thereafter nor does it provide future research directions. Mesmoudi et al. have surveyed localization algorithms in [31], where the algorithms are primarily classified into range free and range based algorithms, each of which are further classified into full schemes and hybrid schemes. Although this work presents a comprehensive analysis of the algorithms, mobility issues are not covered extensively. A survey on mobile sink routing in WSNs is presented by Tunca et al. in [32], however, it does not provide the localization of the mobile nodes. Gu et al. in [33] have presented an up-to-date survey on sink mobility management with recent research progresses. However, it does not provide source localization, and therefore classification and detailed discussion of localization algorithms are absent.

Our work provides an update of all the latest progress on localization techniques in WSNs. From the perspective of parameter definition, classification of algorithms, comparative analysis, application scenarios, and future research directions, our work outlines the whole picture of localization in WSNs which is different from existing state-of-the-art survey papers. In this paper, we present the state-of-art progress of localization algorithms, classification based on lucid definitions, real world applications of localization, and finally, the future research directions. Compared to other surveys that discuss basic centralized and distributed algorithms, we have distinguished the algorithms based on network (e.g. sparse and dense), indoor application, dependence on anchor nodes, and mobility. This extensive classification has made this survey paper unique. Furthermore, the in-depth application section and future research ideas fulfill the demands of a thorough survey paper. Compared to previous work, this survey paper offers the following contributions:

- We provides lucid definitions of different types of localization algorithms in WSNs.
- We presents a comprehensive survey of recent advances on localization algorithms and classify them based on network size and anchor nodes.

- We analyze the positive and negative aspects of all localization algorithms in WSNs.
- We discuss recent algorithms, explaining their mobility properties and issues.
- We include a comparison among the algorithms with respect to different parameters of WSNs.
- We present Details regarding applications of localization, along with future research ideas.

The remainder of this paper is organized as follows: In Sections 2–5 we summarize the localization algorithms. In Section 6, we present some practical applications of localization. Section 7 presents the concluding remarks.

2. Localization in sparse and dense networks

Based on the sparseness of the network, the localization algorithms can be classified as global and sequential. Semi-definite programming (SDP)[34,35] is regarded as the most prominent approach for global localization. Furthermore, multi-dimensional scaling (MDS) is also proposed for optimal global localization [36–38]. Note that these algorithms can compute all the node positions simultaneously in dense networks and are prone to faulty measurements in the sparse networks.

The sequential approaches localize all sensor nodes sequentially [39,40]. To deal with the sparse network, two types of algorithms have been proposed: *node based localization* and *component based localization*.

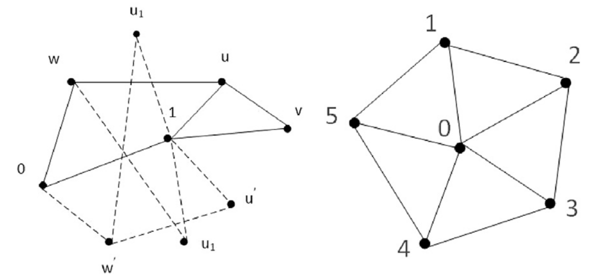
Node based localization algorithms include 'TERRAIN' [41], which is based on trilateration and local maps [38,42]. Furthermore, a collaborative multilateration based algorithm has been proposed in [35] where neighboring nodes collaborate. Since collaboration was allowed only with the neighbors, its performance is limited, as it prunes inevitable measurement errors. Localization schemes introduced in [42,43] alleviate the effects of measurement errors, such as robust quadrilaterals [42]. Although this approach succeeds in ensuring the absence of systematic localization error, it fails to localize properly beyond the local sparsity. In this perspective another algorithm named 'Sweeps' has been proposed in [44], which performs better than the other node based localization methods. Although 'Sweeps' had achieved utmost performance in node based localization, there has been a performance gap between 'Sweeps' and the actual theoretical bound [45].

In component based localization, a component, a rigid structure of a collection of nodes, is used as a basic unit for localization. 'Component bAsed Localization aLgorithm' (CALL) [43] was introduced as a new mechanism for component based localization. Since CALL is based on idealized model, it suffers from measurement errors. To deal with the measurement errors, another scheme called 'Error-TOlerant Component-based algorithm' (ETOC) has been presented in [11].

In the following two paragraphs, we describe the node based localization and component based localization.

2.1. Node based localization

The node based localization based algorithm called 'Sweeps' [44] is related to the iterative method 'trilateration'. In the trilateration method, a primary set of three nodes with fixed location information is used to define a coordinate system. At each stage of the algorithm, there is a set of finitely localized nodes, where nodes can be determined up to a finite set of possibilities, and a set of unlocalized nodes. At each iteration, if an unlocalized node has a distance measurement to at least two finitely localized nodes, its position is calculated for all possible positions for itself based on the consistent combinations of these nodes' positions.



(a) Basic Shell Sweep algorithm. (b) A wheel network with 6 vertices.

Fig. 2. Localization using Sweeps.

Two nodes are said to be consistent if they depend on the same possibility. For example, consider a wheel network as shown in Fig. 2b where the location of v_0, v_1 and v_2 are fixed as $v_0 = (0, 0)$, $v_1 = (a, 0)$ and $v_2 = (b, c)$ with $a, c > 0$. The lengths of v_2v_3 and v_0v_3 compute the position v_3 with binary ambiguity. Then for each of these possible positions of v_3, the information about the length of v_3v_4 and v_0v_4 is found, which eventually calculates the position of v_4 with another binary ambiguity. Therefore, four combinations are possible. In Fig. 2a a basic sweeps algorithm is shown. The sweeps starts from nodes 0 and 1. Node w is finitely localized to the possible positions w and w'. Node u uses the unique position of 1 along with two possible positions of w. w produces the possibilities u and u_1 while w' produces the possibilities u' and u'_1. Since v depends on w, its position is not consistent with u' and u'_1.

For a wheel network of size $k+1$, the position of $v_5, v_6, \ldots, v_k$ can be calculated with $2^3, 2^4, \ldots, 2^{k-2}$ ambiguities. However, since v_k is connected to v_0 and v_1, the knowledge of the associated lengths resolves the ambiguity in the position of v_k. Thus, the ambiguity of every other position can be resolved, and the localization of the network is established.

2.2. Component based localization

In the component based algorithm, a component is defined as a set of nodes that constitutes a globally rigid structure in the distance graph. Because of their rigidity, the relative position of each node in a component is fixed. Unlike the node based localization scheme, the component based localization method directly locates two dimensional components. Component based localization can be classified based on the presence of the internal anchor in each component. In this section, robust realization with one internal anchor and no internal anchor are described briefly.

In the case of one internal anchor, the coordinate system registration cannot be adopted directly. For example, in Fig. 3, the curved area denotes a component, which contains an anchor a_1 and two nodes n_1 and n_2 sharing two edges with two external anchors a_2 and a_3. Let α, θ and ϕ denote the angle values of $\angle a_2a_1a_3$, $\angle n_1a_1a_2$ and $\angle n_2a_1a_3$ respectively. Since all the distances are known, the angle values can be calculated from the $\Delta a_2a_1a_3$, $\Delta n_1a_1a_2$, and $\Delta n_2a_1a_3$, respectively. Defining $S = (\alpha+\theta+\phi, \alpha+\theta-\phi, \alpha-\theta+\phi, \alpha-\theta-\phi)$ and δ as $\min|\cos\beta_1 - \cos\beta_2|$ for all $\beta_1, \beta_2 \in S$ and l_1, l_2 as the in-component distances of node pair (a_1, n_1) and (a_1, n_2) respectively. Therefore, the upper bound of ranging errors for component based localization can be expressed as:

$$T_c = \frac{1}{2}\frac{l_1 l_2}{l_1 + l_2}\delta \tag{1}$$

When there is no internal anchor, five interconnected edges are used to form a system of over-determined simultaneous equations for converting a coordinate system. In Fig. 4, the component con-

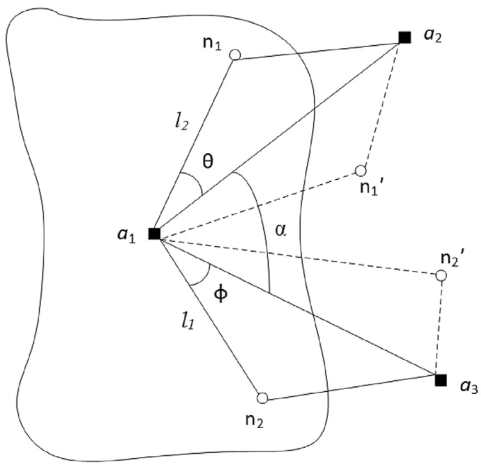


Fig. 3. Robust realization with one internal anchor.

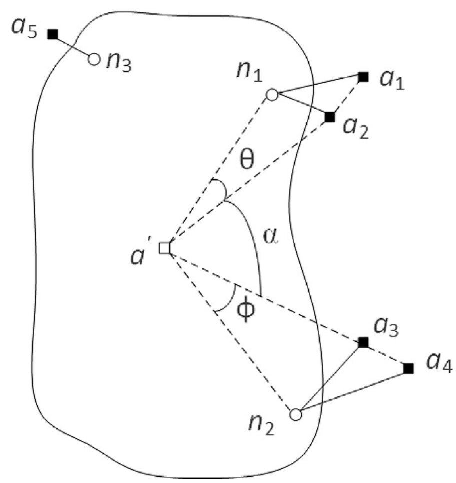


Fig. 4. Robust evaluation by error tolerance.

sists of n_1, n_2, n_3 while n_1 and n_2 share two edges with two external anchors. Anchors are denoted as a_1, a_2, a_3, a_4 and a_5. a' is the intersecting point of a_1, a_2 and a_3, a_4. The angle α can be calculated from $\Delta a' a_1 a_4$. Since $\Delta n_1 a_1 a_2$ and length $a' a_2$ are known, the angle θ and the distance between l_1 and $\Delta a' n_1 a_1$ can be computed. In a similar fashion, ϕ and distance l_2 from $\Delta a' n_2 a_4$ can be calculated. After computing all the unknown angle values and distances, the robustness of the structure can be evaluated by error tolerance. If it is robust, then by using the concept of presence of internal anchor, the component is localized.

2.3. Future research directions

One of the least explored areas of WSN localization is sparseness of the sensor nodes in the network, which is discussed in this subsection.

2.3.1. Consideration of highest-stress configuration

The node-based 'Sweeps' [44] algorithm disregards highest-stress configuration in localization, where stress is defined as the difference between the computed possible positions of two sensor nodes and the noisy measured distance among them along the set of edges. Future research can be directed to consider a highest stress configuration in the localization and provide solution to this issue.

2.3.2. Robust algorithm without in-component anchors

Among the very few research works on localization in sparse sensor networks, Wang et al. in [11] were the first work in robust component based localization in which the issue of noisy range measurement has been discussed, as it can cause structural deformation. More works are required to address component based localization scheme. Moreover, since [11] uses an in-component anchor, future research can investigate robust patterns without any in-component anchors for localization in wireless sensor networks.

3. Anchor based vs. anchor free localization

Based on whether or not a localization algorithm is utilizing the position information of known nodes, algorithms can be classified as "Anchor Based" and "Anchor Free" algorithms, which are discussed in the following subsections.

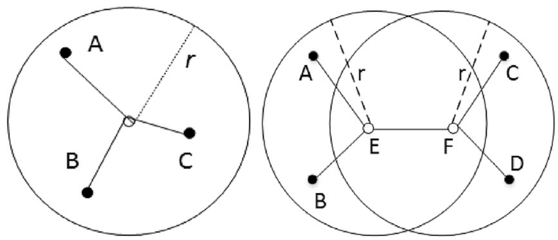
3.1. Anchor based localization

In the anchor based localization technique, few nodes called anchors or beacons are implanted with GPS, which provides these nodes their global position. The nodes with unknown positions collect information from the anchors to estimate their positions by self-localization. Sometimes, these unknown nodes also collaborate with each other and share their mutual position information. This kind of localization is known as remote or cooperative localization. This flow of information is sometimes handled by the individual nodes and sometimes processed by a central processor. This two types of localization based on information processing are termed as distributed and centralized localization, respectively. This information can be about distance measurement or about connectivity, which separate two different subsections of anchor based localization: "Range based" and "Range free" localization methods. Among the discussed anchor based algorithms [19,21,46–49], and [50] use least square, [12,51–55], and [56] use maximum likelihood estimation, [57,58], and [59] use lateration technique, [36] uses multi-dimensional scaling, [22] uses semi-definite programming, [60] uses spectral regression, [61] uses fingerprinting, and [62] uses Monte–Carlo localization for localization of unknown nodes.

3.1.1. Range based approaches

Range-based estimate location by point-to-point distance measurements. Some common distance measurement methods are angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), acoustic energy, and received signal strength indicator (RSSI). The first three methods require complex hardware set up while RSSI is simpler than the others but less accurate. After gathering the information of anchors and sometimes of other unknown nodes, distances are combined using techniques like lateration or particle filter etc.

A range based distributed localization algorithm using MDS is proposed in [36]. In this approach, using classical MDS and iterative MDS, local maps of the adjacent sensors are constructed. MDS utilizes the pairwise distances between the nodes to calculate the location of the sensors, and the iterative approach is adopted when distances between the node pairs are unavailable. After implementation of MDS to build local maps, the alignment method is applied to stitch the maps. Using the RSSI and its relation with the distance measurement, the relative position between nodes can be approximated. The alignment starts with the distance measurement from a starting anchor node and gradually floods the whole network while other anchor nodes are placed at the boundary. Thus, the position estimation is propagated from a starting anchor node to the ending anchor nodes. While the position of an unknown node is estimated, it is considered as an anchor node for position estimation for other nodes. In the small areas, to conserve time and



(a) Classical MDS. (b) Iterative MDS.

Fig. 5. MDS based techniques.

energy, a modified version of distributed localization, On Demand Distributed Position Estimation, was also proposed, based on MDS for one or several adjacent sensors locations. The simulation results show that although this iterative MDS method showed similar robust behavior to distance measurement error like classical MDS [63], they also show that increasing the number of pairwise distances does not increase the error rate, whereas in classical MDS it did. In Fig. 5a classical MDS is explained where *A, B, C*, and *D* are four adjacent sensors and *r* is the radio range. Among the sensors *A, B*, and *C* are nodes with known location. *D* collects the location information of *A, B*, and *C* and calculates the pairwise distances as well as the distances of *D* to *A, B*, and *C* respectively. Thus *D* performs a classical MDS. On the other hand in Fig. 5b, *A, B, C, D, E*, and *F* are six adjacent sensors and *r* is the radio range. *E* and *F* are the only nodes with unknown positions. *E* collects the position information of *A, B* and their distances to them. Similarly *F* collects the position information of *C, D* and their distances to them. Moreover *E* broadcasts the collected distance information to *F*. In this way *F* can gauge the pairwise distances of the six sensors excluding the distances of *AF, BF, CE*, and *DE*. Thus *F* can perform an iterative MDS to build a local map.

The researchers in [46] discuss the range based source localization problem in which distance measurement of the path loss model has been formulated as a ratio of two powers. In the conventional path loss model, RSS value can be modeled as:

$$R_i = R_0 - 10n\log_{10}(d_i/d_0) + X_i \tag{2}$$

where R_0 is the source transmitting power, R_i is the measured RSS at the receiver, and n is the path loss exponent. In unknown environment both R_0 and n are unknown, which make the proper location computation a very difficult task. In this research work, the model has been simplified into such a position where only path loss exponent, n, is the unknown parameter. Using a search method within a specific boundary, the path loss exponent is found and the source location is estimated implementing linear least squares. This localization scheme has been compared to centroid and linearization methods. It has been found from the simulation outputs that the proposed method performs better than other two since its localization accuracy does not deteriorate due to various geometric conditions.

A received signal strength indicator (RSSI) based localization technique using cognitive sense has been proposed in [51] and is known as cognitive maximum likelihood (C-ML). At first the nature of the environment is judged on whether it is homogeneous or non-homogeneous. A hypothesis testing is then derived called generalized likelihood ratio test (GLRT). Based on the output of the GLRT test, an appropriate ML-based localization algorithm, either homogeneous maximum likelihood (H-ML) or non-homogeneous maximum likelihood (NH-ML) is selected. Separate propagation parameters are derived for both scenarios. The performance of the proposed algorithms has been compared by extensive simulations. Simulation results confirm that both C-ML and NH-ML localizers perform well in both homogeneous and non-homogeneous environments. Furthermore, the NH-ML and H-ML localizers show similar performance when the number of observations and number of anchor nodes are higher in a homogeneous environment. Oğuz-Ekim et al. propose a range based maximum-likelihood (ML) algorithm in [22]. The core idea is to devise a source localization method by constructing a ML estimation problem followed by convex relaxation of ML through SDP. Source localization in complex plane (SLCP), a 2D localization previously proposed in [64], is the reference for the novel idea while the new SDR method is designated as source localization with nuclear norm (SLNN) considering the Gaussian noise. Similarly, another improved version of [65] for Laplacian noise is also presented, termed SL-l_1. Along with basic 2D and 3D, higher dimension scenarios are also considered for the proposed frameworks. The simulation results confirm that the constant behavior of proposed l_1 based algorithms and Laplacian noise based algorithms performed better than others.

An energy-efficient range based localization has been proposed by Yaghoubi et al. in [47]. In this locallization technique, the average energy of the received anchor is introduced as a new decision metric for the localization. The localization algorithm has been proposed to show a relationship with the power allocation of the anchor nodes. Two cases were considered: localization assuming error free anchor nodes location and localization considering the erroneous anchor nodes position. Through mathematical computation, it is proven that localization accuracy can be regulated by different power allocation of the anchor nodes. The simulation results support the mathematical derivation presented in this study by showing that optimal power allocation performed better than the equal power allocation algorithm both in error free and erroneous anchor position cases.

A range based localization model that considers a Bayesian approach has been proposed in [19]. Instead of a conventional path loss model, this work presents a ranging measurement using a Bayesian model. To devise a model that needs less prior information, this research work adopts the 'Empirical Bayes' [66,67] approach. The advantage of this 'Empirical Bayes' is that it requires less conditional prior knowledge. To find the Bayesian estimation more easily, some conditions are applied. In this method, a minimum mean square error (MMSE) estimator is derived for final estimation as conditional mean. The estimator includes a shrinkage factor that corrects the range measurement. For the positioning, this algorithm uses iterative least square (ILS) rather than lateration. ILS updates the estimated position of unknown nodes through iterations. Through the simulations this mechanism is compared to other contemporary methods. The MMSE performs better than the path loss model (PLM), and ILS performs better than lateration. This mechanism is also compared to range-free ML estimation, which requires numerical optimization. Simulation results also reveal that the proposed method is close to the ML estimation based method in terms of performance. Furthermore, this scheme is innately robust due to its shrinking factor.

3.1.2. Other range based approaches

A semi-3D range based localization scheme has been proposed in [48]. This algorithm utilizes Heron's formula of tetrahedron to compute the height of the unknown node. This method calculates the distances between nodes and the anchors as well as the mutual distances of the anchors. Such distances form a tetrahedron whose volume can be calculated using the Heron's formula. Due to the implementation of the tetrahedron, only three anchor nodes are required for the localization. A necessary transformation of the coordinate systems is done using the transformation matrix to specify an arbitrary point in 3D. Finally, a 2D linear least square estimation (LLSE) [68] is performed to localize the unknown node. To evaluate the performance of the proposed scheme, it was compared to the conventional 3D LLSE and 3D Levenberg–Marquardt

(LM) [69] method. From the simulation results, it is evident that while localization accuracy of 3D LLSE is better than that of 3D LM, the localization accuracy of the proposed method is better than that of 3D LM. Moreover, since the proposed method considers anchor nodes of similar height it does not suffer from the singular matrix problem like 3D LLSE, and its unreliant behaviors on iteration and initial location measurement have made this method simpler than 3D LM.

A comprehensive discussion on the different scenarios of ML based localization and a novel non-convex estimator is presented in [21]. In the ML based localization approach, the multiple local minima of the non-convex objective function in an ML estimator is a crucial problem for formulating a localization algorithm. In this research work a new non-convex maximum likelihood estimator is proposed along with the employment of convex relaxation to relax the proposed estimator. Different techniques has been applied for different localization algorithms. Second-order cone programming (SOCP) is applied for non-cooperative localization and SDP for cooperative localization. It also considers the case of unknown source transmission power and path l'oss exponent for both non-cooperative and cooperative localization. Performance of the proposed algorithm has been tested with other existing approaches. Simulations are conducted for both noncooperative and cooperative scenarios with different parametric variations: a localization scenario in which source transmission power P_T is known, in which source transmission power P_T is unknown, and in which both source transmission power and path loss exponent γ are unknown. The noncooperative localization method outperforms existing localization schemes with regards to estimation accuracy while error is reduced up to 15% in the case of known P_T. Furthermore, in the case of unknown P_T and γ, this scheme also performs better than other methods. It is observed that with the increment of the number of anchor nodes, the proposed method shows more improved results. Although the cooperative localization scheme is more complex than the noncooperative case, it still outperforms other techniques. The increased number of source nodes still provides good estimation accuracy, thereby proving this proposed method to be a better localization method than other state-of-art methods.

An acoustic energy based localization method has been proposed in [52] with an objective to improve the accuracy of the maximum likelihood energy based acoustic source localization. During the process, acoustic noises corrupt the source signal, and the correlation degree of the corrupted signal is represented by Hurst exponent [70]. Theoretically, Hurst exponent is illustrated by the decaying rate of the auto-correlation coefficient function. Acoustic energy of a sample signal has been formulated and further modified to derive a compact form of acoustic source localization model. Hurst exponent estimation examines the correlation degree of the noisy signals, and the wavelet-based method [71–73] is typically used to estimate the Hurst exponent. In the proposed scheme signal samples are represented by fractional Gaussian noise (fGn), which models any degree of correlation using Hurst exponent and energy measurement error. fGn is produced by applying the midpoint displacement scheme [74]. From the simulation results, it is proven that fGn is a better way of representing the correlation among the received signals. The estimation process is named as 'H-ML-Energy' localization estimation, which calculates maximum likelihood estimation function using a gain matrix, an attenuation matrix, an acoustic energy source vector, and an error vector. Joint probability density function is the next step derived from the maximum likelihood estimation matrix. Finally, the log-likelihood function is formulated from the density function. The minimum value of this log-likelihood function could be found using multiresolution search [75] or exhaustive search. In the simulation three sources (Car, Helicopter, and Speech) and three noises (Babble, Car, F16) are used in the Monte Carlo experiment for the evaluation of the proposed method. To measure the accuracy of the scheme, three different parameters are used: error probability distribution, Bhattacharyya distance, and root mean square error (RMSE). The results show that the proposed approach performs a lot better than baseline ML-Energy in the presence of a noisy atmosphere.

Shen et al. present a new research work in [49] to discuss the concept of multiple source localization. This algorithm adopts ToA measurements among the nodes and the optimization technique to address the problem of multiple source localization. ToA measurement vectors can be represented by an optimization consisting of a mixed integer problem and three norms (l_2-norm, l_1-norm, l_∞-norm), based on different design criteria. A three step approach has been proposed in the idea to solve this complex optimization problem. In the first step, the conventional integer problem is relaxed into a continuous problem, and then a convex optimization algorithm is applied to solve it. The output from the first step is a course measurement, which is then improved in the second step by utilizing the attained association information. In the second step, the permutation matrix, found in the first step, is modified. Finally, in the third step, the problem is divided again into multiple subproblems, and the results from the first step are used as initial values in the third step, eventually improving the localization accuracy. Simulations have been conducted to determine the feasibility of the discussed research work. It is observed that the performance gap between this proposed algorithm and genie-aided algorithm is very small even for high SNR. Among the three norms, l_2-norm performs best while l_1-norm performs better than l_∞-norm. The measurement technique adopted in this algorithm is ToA. This is compared with two other techniques, the first case of which one sensor node is used as the reference node to calculate TDoA and the second case of which all sensor nodes are used. Simulation results prove that the ToA based algorithm outperforms the first setup and shows similar performance to the second setup.

An anchor based localization using dual embedding spectral regression (DESR) has been proposed by Gepshtein et al. in [60]. In this new concept, DESR has been proposed in order to compute an adaptive base by computing the dual embedding of the network distances. According to the dual embedding, the input noisy distance measurements are first embedded by diffusion embedding [76,77], which is followed by Isomap embedding [78]. To improve localization another approach, augmented dual embedding spectral regression (ADESR), is also proposed, which augments the number of distance measurements by implementing patch-based localization schemes [79–81]. To verify the added distances, 'Triangular Inequality' is applied as a preprocessing step for the input distance measurements, which finds error probability of a node position. Extensive simulations are conducted to prove the superiority of the proposed method over the other state-of-art methods. This algorithm is compared with ASAP [79], ARAP [81], SR [76] and SDP-SNL [82]. When ADESR is compared with ASAP and ARAP, the nodes are connected to each other, and the number of anchor points are 30. At low noise level, the performance of the proposed method is similar to the other two schemes, but with the increment of noise level, the accuracy of ADESR increases significantly compared to ASAP and ARAP. Similarly, different variations of ADESR show better performance than SDP-SNL with the increment of noise level. When comparing the ADESR with SR in the nonconvex domain, the results prove again the superiority of the proposed scheme. Fig. 6 illustrates the computational augmentation of network distances. Here two network strips are localized in order to estimate the distance $d_{5,\,14}$.

A cooperative (non-Bayesian) localization, proposed by Yin et al. in [53], adopts expectation-conditional maximization (ECM) criterion to approximate the ML estimator of unknown sensor loca-

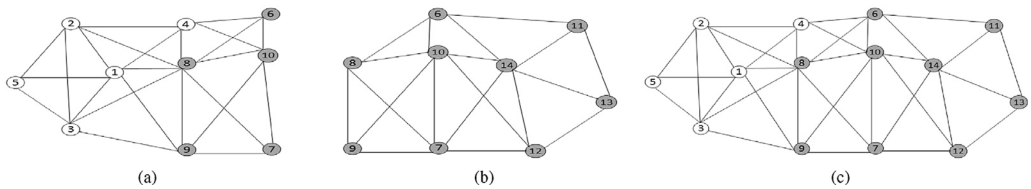


Fig. 6. Augmentation of network distances. Two network patches (a) and (b) are localized to measure the distance $d_{5,13}$.

tions. This work is an extension of the previous work done by the same research group in [83]. The proposed model represents the measurement error distribution by Gaussian mixture parameters. In this research work one centralized ECM and two distributed ECM algorithms are presented. In the centralized ECM algorithm, a two-dimensional (2-D) Broyden–Fletcher–Goldfarb–Shanno (BFGS) Quasi–Newton (QN) method [84] is applied for position estimation of sensor nodes. In the first distributed algorithm, to make the algorithm scalable, synchronous average consensus algorithm [85] is applied assuming that sensors are time-synchronized. On the other hand, the second distributed ECM algorithm 2-D BFGS-QN or 1-D GS method is implemented to compute the position as the positions are updated simultaneously. Simulations have been done to compare the proposed algorithm with some state-of-art methods such as distributed LS algorithm [20], classical SPAWN algorithm [20], and its variations [86,87]. Simulations are intended to compare the performance among these algorithms with respect to variable network size and measurement error statistics. When the network size is large, ECM algorithm outperforms distributed LS algorithm and is similar to the classical SPAWN algorithm. Again, ECM shows significant performance compared to the parametric SPAWN algorithm [87] when sensors are greater than 100. On the flip side, ECM is proven to be less suitable for smaller network size. This ECM algorithm has been further experimented upon with varying different network topologies and measurement error statistics. Results imply that overlap of the Gaussian mixture model might degrade the performance. Hence, compared to a Bayesian approach like SPAWN [20], this non-Bayesian algorithm performs closely without demanding any precise measurement error statistics or complex NLOS identification.

Another cooperative localization approach has been proposed in [50]. Firstly, this research work derives a Fisher information matrix (FIM) considering the NLOS ranging bias model. Among two extreme cases, Gaussian proves to be the worst due to NLOS effect while constant bias shows the best result to be almost equivalent to full LOS condition. Position error bounds (PEB) of three separate localization algorithms (least square (LS), squared-range LS (SR-LS), squared-range weighted LS (SR-WLS)) are computed and then found that LS and SR-WLS are asymptotically efficient. Finally a distributed algorithm is designed with a combination of squared range relaxation and variational Bayesian inference based variational message passing (VMP) [88]. To examine the performance of the network in the stochastic manner, Gilbert's disk localization [89] is implemented in which Gaussian measurement noises and LOS are homogeneous in nature. Generalized trust region subproblem (GTRS) technique [90], generally used in non-cooperative localization, is also adopted in the proposed distributed cooperative localization. The simulation results indicate that the distributed version of the cooperative algorithm is more cost effective in terms of message exchange and time consumption when compared to the centralized one.

The researchers in [12] propose an algorithm that proves the mobility information of nodes can improve the accuracy of a localization scheme. This algorithm uses two types of range measurement technique, ToA and RSS. At first, a ML estimator is derived considering error free velocity measurements for the ToA based range measurement model. Two different approaches of SDP relaxation are used to relax the obtained non-convex objective function. Then the SDP relaxation technique is applied for a noisy velocity measurement. The same procedure is continued for the RSS based range measurement model. Simulations have been conducted for both ToA and RSS range measurements considering two different measurement scenarios: error free velocity measurement and noisy velocity measurement. It has been found that the increment of anchor nodes and radio range improves the localization accuracy. Furthermore, it has been shown that the maximum velocity of a movement has more effect on the accuracy of the localization than the number of anchor nodes and radio range. Similarly from the simulation results of RSS based measurement model, velocity of nodes is proven to be the most significant factor in the accuracy of the proposed scheme.

Another iterative distributed localization algorithm has been proposed in [58]. In this work, the node's position is represented in the barycentric coordinate system [91], which is introduced as a geometric notion characterizing the relative location of a point with respect to other points. This research idea is motivated by the 'Distributed Iterative LOClization' (DILOC) method [92,93], in which sensor location can be represented as a pseudo linear system. This proposed method in [58] is different from the typical DILOC method since each sensor does not have to lie inside the convex hull of its neighbors, as it is not suitable from a practical point of view, especially in the case of large sensor networks. A typical DILOC algorithm may not converge due to the instability of generalized barycentric coordinates. To overcome this problem, an iterative distributed algorithm termed 'Extended Computation scHeme of cOordinate' (ECHO) is devised to solve the problem of unstable matrix formation in the DILOC algorithm, thus ensuring the global convergence exponentially. Finally, simulation results confirm its superiority over MDS based localization algorithm.

Researchers in [94] have proposed a novel localization algorithm based on the data fusion technique 'Dempster–Shafer' (DS) theory, a dynamic generalization of Bayesian probability theory. In this proposal, in addition to RSS and AoA a unique technique named Standby has been adopted along with a significant feature of DS theory named the basic probability assignment (BPA). The concept of BPA includes belief and plausibility, representing accordingly the best and worst case scenarios. A BPA has three important properties, lower bound, upper bound, and confidence. The proposed algorithm starts with the regular collection of the distance measurements RSS, AoA, and standby distance. Then the following procedure is continued for each observation per feature. After filtering the data the minimum and maximum values are considered as the lower and upper bounds of the BPA. In the next step, after sampling all the BPAs, they are aggregated. Since the BPAs are aggregated, the third property of BPA, confidence, is assumed as 1. After the aggregation, the most plausible distance has been predicted along with lower and upper bound of it. Finally, the measured value and the most plausible value are compared for a more accurate localization.

3.1.3. Range free (non-range based) approaches

Range free localization algorithms use connectivity information among the nodes to determine the positions of unknown nodes. Since the range based methods require a hardware setup that is both complex and costly, a range free method can be a possible solution to hardware limitation problems. Recently proposed anchor based range free localization algorithms are discussed in this subsection.

Wang et al. in [11] have proposed a range free localization algorithm as an improvement to regular DV-Hop algorithm. The idea of regulated neighborhood distance (RND) has been proposed in [95], using the *disk communication model* for localization. In [11] the RND concept had been revisited and revamped with an attempt to apply RND in the *general propagation model*. The main objective of the RND algorithm is to fix the problem of hop-distance ambiguity by measuring the proximity of two neighboring nodes. In this algorithm, packet reception rate (PRR) is used as a parameter to define 'hop' and 'neighboring node'. A node i is the neighbor of node j if the PRR at node i from the node j is not smaller than the PRR threshold (γ). The first step of localization using this algorithm is to compute the shortest RND of all pairs of anchor nodes, which is determined with the Floyd–Warshall [96] algorithm. Then the correction factor is computed, which measures the network-wide distance-per-hop. After that, distances between anchor nodes and unknown nodes can be determined. Trilateration algorithm is used to estimate the position of an unknown node after the distances from three anchors to the unknown node are determined. Measurements in all these steps depend on the proper consideration of number of localization packet T and PRR threshold γ. Due to the adaptive property of the proposed algorithm, it is termed as DV-ARND localization. The proposed algorithm has been compared with the DV-Hop and DV-Distance algorithm [97] through simulations. Simulation results confirm that DV-ARND outperforms DV-Hop algorithm under both log-normal shadowing and polynomial fitting model. It is observed that when the number of nodes is increased, the performance of DV-RND improves further.

An improvement on the ML based localization method has been proposed in [55], discussing the issue of non-synchronized sensors. It adopts ToA of the arbitrary signals, and it suggests a convex method to overcome the problem of convergence to the local minima by using an iterative method to find the optimum global minimum through iterations. To estimate the clock offsets and source position, an iterative ML estimator is presented that insures a non-increasing cost function after each iteration. For synchronization using convex optimization, maximum volume inscribed ellipsoid (MVIE) [98] is implemented. The implementation of MVIE along with ML reduces the number of iterations required for the iterative ML to converge. Simulation results also confirm that MVIE initial guess reduces the number of iterations required for the convergence of the iterative ML estimator.

Lasla et al. propose an area-based localization algorithm in [99], where a novel technique half symmetric lens (HSL) is introduced. Rather than using conventional circular or ring based shapes, authors use a shape called symmetric lens or Vesica piscis [100]. To exchange information among the nodes, RSSI is used. A symmetric lens shape is created for each pair of anchor nodes and divided into two halves. Then it is calculated whether a node is inside a half or not by comparing the RSSI values among the nodes. To estimate the coordinates of the nodes, this method adopts a grid scan algorithm to measure an approximated area. To overcome the problem of a non-localizable node, HSL divides the whole area into a set of disjoint regions utilizing Voronoi tessellation [101]. The non-localizable node can find its position among one of these regions by comparing the heard information from different anchors. To analyze its performance this algorithm has been compared to APIT, ROCRSSIA, and a circular based algorithm DRLS [102], considering a ratio of localizable nodes and estimation error as the comparing parameters. *Ratio of localizable nodes* is defined as the percentage of nodes accurately located in the residence area, and *estimation error* is defined as the difference between actual and estimated distance of a node. Comparing with respect to *ratio of localizable nodes*, HSL outperforms other algorithm even if they all use the Voronoi technique. This is mainly due to the basic half symmetric lens shape used by the HSL. Similarly, in terms of *estimation error* HSL prevails over other mentioned algorithms because of the usage of the geometric shape by HSL, which produces a smaller residence area. Moreover, HSL performs even better than DRLS at the presence of noise. Fig. 7 has illustrated the area construction according to HSL algorithm. In this figure, A_1, A_2, and A_3 are three anchor nodes, and S is the node to be located. The network can be divided into three sub-areas $VNA(A_1)$, $VNA(A_2)$, and $VNA(A_3)$ according to Voronoi diagram. Initially node S locates itself in cell $VNA(A_1)$, but later it considers the distance and RSSI values from two other anchors and refines its residence area.

A maximum likelihood based distributed localization algorithm has been proposed by Simonetto et al. in [54]. In this research paper, a ML based convex relaxation has been proposed with a detailed description of its characteristics. The ML based relaxation has been examined for different noise distributions like Gaussian noise relaxation, quantized observation relaxation, Laplacian noise relaxation, and uniform noise relaxation. The ML based relaxation method is further massaged into an edge-based ML relaxation method. Based on the edge-based ML relaxation, a distributed algorithm has been proposed that employs the alternating direction method of multipliers (ADMM) [103,104]. ADMM is chosen due to its noise and error resilient nature and because very few assumptions are required to ensure the convergence. The algorithm is compared with two other distributed algorithms: sequential greedy optimization (SGO) [105] and distributed maximum variance unfolding (MVU) [106]. The comparative analysis among these three algorithms reveal that the proposed algorithm is best in terms of good convergence rate with a reasonable communication cost and especially suitable for large scale networks.

A fingerprinting based decentralized localization algorithm DWKNN is presented in [61], which adopts accelerometer information for better accuracy. This method completes the localization of an unknown node in two steps. In the first configuration step the area is divided into several zones where an RSSI fingerprint is used to form local maps for each zone. Then using the nearest neighbor (NN) [107,108] algorithm, the location of the nodes is estimated. The local maps are gradually converted into a global map after each time step. To improve the global estimate, mobility information of some selected nodes are used in this localization algorithm. For the implementation of mobility information two methods are adopted: interval analysis [109], which estimates the position by considering all possible solutions and Kalman filtering [110], which uses accelerator information to predict the position and corrects them later using radio fingerprinting. The methods are termed DWKNN-I and DWKNN-K, respectively. This proposed algorithm has been compared with other recent localization algorithms, which includes range based, connectivity based, and fingerprinting based algorithms. In the simulation environment, both versions of the proposed algorithm outperform the concurrent algorithms.

A novel historical-beacon aided localization method has been proposed in [62], which exploits a historical beacon together with a current beacon to estimate a node's position. This method can be divided into three phases. In the first sample, generating a phase possible region of a node's location is estimated by finding the intersection of the one-hop-anchor constrained regions with the historical-anchor-constrained region. A constrained region is defined as an area that covers the location of a regular target node.

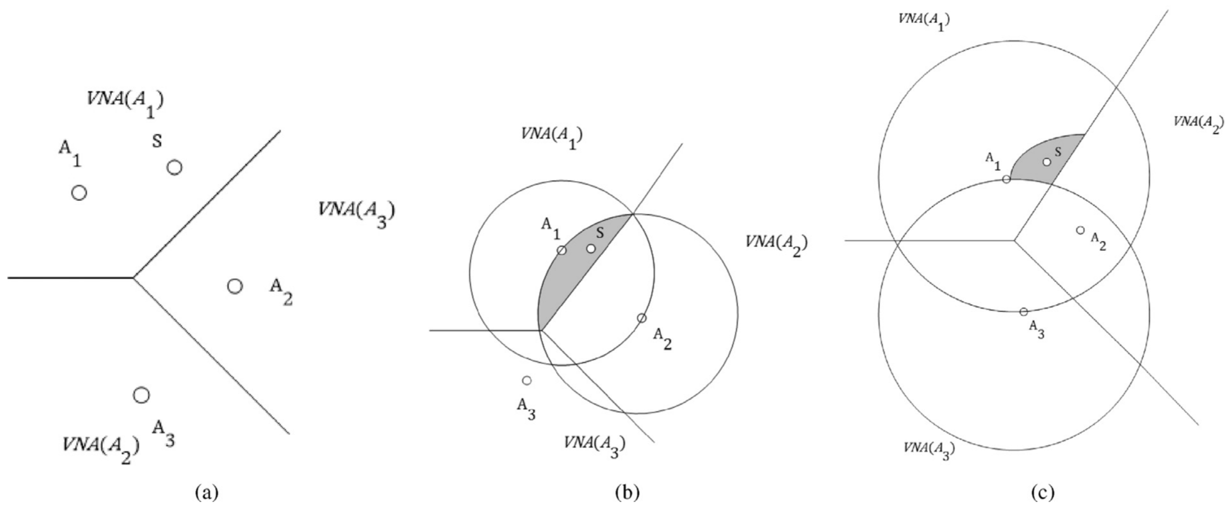


Fig. 7. Area construction in HSL. (a) shows the first consideration of node *s* residing in *VN*(A_1). (b) shows modified residence of *s* as *HSL*(A_1, A_2) after the consideration of *RSSI* values. (c) shows the final refined residence area considering other anchors.

In the second phase, the sample filtering phase, invalid samples are filtered by means of three proposed RSS based constrained regions. These regions are constructed using the beacon pairs from both types: current beacon and historical beacon. Depending on their combinations, the three formed regions are: current-current-RSS-constrained region (CC-region), current-historical-RSS-constrained region (CH-region), and historical-historical-RSS-constrained region (HH-region). At the last location estimation phase, the location of a unknown node is estimated as the centroid of all valid samples.

In [59], the researchers propose a multi-hop localization technique with an objective to solve the complex localization problem of the Amazon River. The thick forest structure and the mobility of sensor nodes make the problem difficult and complex in devising an accurate localization method. To form the network, network formation packets are flooded among the anchor nodes. In this network topology formation, a sensor node can act both as an anchor and a sensor node while continuously exchanging the packets with the anchor nodes. Since the sensor nodes drift with the current of the river water, their mobility pattern cannot be depicted by the conventional mobility model. In this research work, the movement of the sensor nodes is modeled by a standard stream function [111]. Each sensor node collects the data about its direct neighbors and their corresponding weights. To estimate the position, each sensor node updates its weight value locally, which confirms the distribution of each anchor information in its nearby areas. The basic reason to update the information locally is to adapt to the continuously changing network topology along with the node mobility. Each sensor node's weight values are collected for three anchors, and its relative distance is computed according to the one-hop distances and their weights. Finally, when a sensor node is affiliated with multiple anchor nodes, its location is estimated using the lateration technique.

The abbreviations of the metrics used in the following comparison tables are listed in Table 2 and the comparison among the anchor based algorithms is given in Table 3.

3.2. Anchor free localization

Anchor-free localization algorithms do not depend on the location information of some certain nodes to evaluate the actual position of unknown nodes. These algorithms have freedom on translation and orientation. Based on the usage of the range measurement technique, these localization algorithms are divided in two ways: range based anchor free and range free anchor free. Anchor free localization algorithms do not require the anchor selection process, which is very complicated. In the following two sections, anchor free localization algorithms of range based and range free types are discussed in detail. [42] adopts trilateration, [41] uses triangulation, and [112,113] adopts multi-dimensional scaling for localization. Furthermore, [114,115] utilize both multilateration and MDS for localization.

3.2.1. Range based approaches

This type of algorithm uses measurement information between nodes. The distance can be measured based on criteria such as ToA, TDoA, acoustic energy, or RSSI. The anchor free algorithms based on range based measurements are also known as cooperative localization.

In [41] the researchers present an anchor free localization method using the range measurements. An algorithm known as assumption based coordinates (ABC) is presented to determine the local position of each node. According to this methodology, a node receives information about the range measurements from a large number of neighboring nodes, which is later used to correct errors that happen during the local positioning. For global localization each node shares its local position with the neighboring nodes, eventually forming a single global map. An anchor based algorithm, triangulation via extended range and redundant association of intermediate nodes (TERRAIN), is also discussed in this research work. TERRAIN uses ABC in each anchor node and transmits them to the other nodes to construct global mapping of the nodes. An iterative local triangulation is also suggested for better location accuracy.

Priyantha et al. propose an anchor free distributed localization, anchor-free localization (AFL) in [18], emphasizing the fold-freedom of the nodes. Fold-free graph construction of nodes is defined as the proper orientation of the nodes after every global translation. Constructing a fold-free contour of the nodes is the first step of AFL initiated to solve the problem of false minima. Five nodes are selected as reference nodes in such a way that four of them are on the boundary while the fifth one is in the middle. In the second step, the mass-spring optimization technique is applied to exchange the position information amid the nodes for better localization accuracy, which results in a low probability of converging to a local minimum. While comparing the performance of the AFL algorithm with the incremental scheme, it is found that the proposed AFL algorithm performs better even with small connectivity and shows good accuracy.

Table 2
Summary of abbreviations.

Acoustic	Acoustic signal	**M**	Medium
BRL	Bayesian Ranging Based Method	**MCL**	Monte Carlo Localization
Centra	Centralized	**MDS**	Multi-Dimensional Scaling
CF	Curve Fitting	**MSL**	Multiple Source Localization
Co	Cooperation among nodes	**Multila**	Multilateration
Coop	Cooperative	**N**	No
Connect	Connectivity	**ND**	Node's Density
CS	Compressive Sensing	**NM**	Node's Mobility
Distri	Distributed	**NonCoop**	Non-Cooperative
EEL	Energy Efficient Localization	**NS**	Not-Specified
EKF	Extended Kalman Filter	**PL**	Passive Localization
FP	Fingerprinting	**RA**	Residence Area
Geo	Geometric	**RC**	Range Combinations
H	High	**RM**	Range Measurement
IEL	Interpolation-Extrapolation based Localization	**RSSI**	Received Signal Strength Indicator
ILS	Iterative Least Square	**Sc**	Scalability
IML	Iterative Maximum Likelihood	**SDP**	Semi-Definite Programming
KDE	Kernel Density Estimation	**SOCP**	Second Order Cone Programming
KNN	K-Nearest Neighbor	**SR**	Spectral Regression
L	Low	**TDoA**	Time Difference of Arrival
LAc	Localization Accuracy	**ToA**	Time of Arrival
LLSE	Linear Least Square Estimation	**ToF**	Time of Flight
LM	Localization Method	**Triang**	Triangulation
LS	Least Square	**Trilat**	Trilateration
LWUPLM	Localization With Unknown Path-Loss Model	**Y**	Yes

Table 3
Comparison among "Anchor Based" localization algorithms.

Localization algorithm	RM	RC	ND	LM	Sc	NM	Co	LAc
Distributed MDS [36]	RSSI	MDS	M	Distri	Y	N	Coop	M
LWUPLM [46]	RSSI	LS	M	Distri	Y	N	NonCoop	M
EEL [47]	RSSI	LS	M	Distri	Y	N	NonCoop	M
SLNN [22]	ToA	SDP	M	Centra	N	N	NonCoop	H
LLSE [48]	RSSI/ToA	LS	M	Distri	Y	N	NonCoop	M
C-ML [51]	RSSI	MLE	M	Distri	N	N	NonCoop	H
SOCP+SDP/SOCP [21]	RSSI	LS	M	Centra	Y	N	Coop+NonCoop	H
fGn [52]	Acoustic	MLE	M	Centra	Y	N	NonCoop	H
MSL [49]	ToA	LS	M	Centra	Y	N	NonCoop	M
BRL [19]	RSSI	ILS	H	Centra	Y	N	NonCoop	M
DESR [60]	Connect	SR	M	Centra	Y	N	Coop	H
Distributed ECM [53]	ToA	MLE	H	Distri	Y	N	Coop	M
Distributed LS [50]	NS RM	LS	H	Distri	Y	N	Coop	M
Moblity-Aided SDP [12]	ToA+RSSI	MLE	M	Distri	Y	Y	NonCoop	M
DV-ARND [57]	Connect	Trilat	H	Distri/Centra	Y	N	Coop	H
PL [55]	ToA	IML	M	Distri/Centra	Y	N	NonCoop	M
HSL [99]	RSSI+Connect	RA	M	Distri	Y	N	NonCoop	H
ADMM [54]	Connect	MLE	M	Distri	Y	N	Coop	M
ECHO [58]	NS	Trilat	M	Distri	Y	N	Coop	H
DWKNN [61]	RSSI	FP	L	Distri	Y	Y	NonCoop	H
HitBall [62]	RSSI	MCL	M	Distri	Y	Y	NonCoop	M
M-Mobility [59]	Connect	Multila	M	Centra	Y	Y	Coop	M
DS Theory [94]	RSS+AoA	Trilat	M	Centra	N	N	NonCoop	H

Moore et al. propose a range measurement based anchor free localization algorithm, 'RObust Distributed network Localization with noisy range measurements' (RODL), in [42]. In this research idea, both the flip ambiguity and the noisy measurement are considered. It adopts a cluster based localization, which uses quadrilaterals to avoid flip ambiguities. The overall functionality of this algorithm can be divided into three phases. The first phase completes the cluster localization by keeping each node in the center. Through the overlapping of the quads, the largest subgraph is found. Position of the nodes is determined by the sequential calculation of the quadrilaterals. In the second cluster, formation is improved by usage of numerical optimization. In the last phase, all the local clusters are combined using the common nodes among the clusters. This research work also considers the mobility issues. Since the mobile localization has more noise than static localization, it uses least square optimization for position estimation.

3.2.2. Range free approaches

Several range free localization techniques have adopted anchor free node distribution for more realistic consideration of a localization problem. In the last few years, researchers have been developing a substantial amount of algorithms for range free anchor free localization. These algorithms are based on MDS and 'map stitching', including some hybrid approaches. The core idea of these algorithms is explained below:

The research work in [112] presents MDS-MAP as a possible solution to the anchor free localization problem. The overall algorithm can be outlined in three steps. In the first step, the shortest path between all pairs of nodes are calculated to make a distance matrix. Distances between nodes are computed using proximity information. Proximity information might be obtained from a radio or sound source, wherein proximity information can be enhanced using distance measurement. Utilizing this distance matrix, MDS constructs a 2-D or 3-D map, which depicts the relative position of all nodes in the second step. Finally, with the help of known positions of some nodes, information about absolute location can be computed from relative positioning of the nodes. For the absolute location of the nodes, it requires only three anchor nodes when nodes were placed in a grid and four nodes when nodes are placed randomly with a position error less than 50% of the radio range. This algorithm performs better than other similar algorithms like DV-Hop or Hop-TERRAIN in the case of low anchor nodes. However, as the number of anchor nodes gets larger, this algorithm does not perform as well as the other algorithms.

An improved version of [112] has been proposed in [113], in which centralized MDS-MAP has been transformed into distributed MDS-MAP(D) using the concept of positioning using local maps (PLM). At the primary stage of this algorithm, each node computes its local map using MDS-MAP [112]. All the local maps are then connected based on the pair of adjacent nodes common among those local maps. Then, the position of each node is determined with respect to the center node. During the alignment of the local maps, an optimal linear transformation is calculated for the transformation of the common nodes from one map to another. From there, least square minimization is used to minimize the distances between the neighboring nodes. For the calculation of absolute position, a mass-spring model is utilized to refine its position with respect to its neighbor's calculated position. Simulations have been conducted to compare this algorithm with APS and MDS-MAP(P), which is an improved version of MDS-MAP performed on irregular topologies. Simulation results show that MDS-MAP(D) performs well both in regular and irregular shaped networks if connectivity is ranged from medium to high.

A map-stitching based localization has been proposed in [114]. According to this algorithm, a local map is formed for each component of the network. For the construction of local maps both multilateration and MDS based methods are considered. The second step is the stitching of local maps. The first contribution of this work is to devise a method for map-map stitching. For the stitching purpose, a core node is selected based either on some criterion or randomly. The local maps are coined as primitive maps, which then participate to form a core map. After the selection of core maps, all primitive maps are stitched to the core map in succession. This algorithm proposes several methods based on distinct stitching conditions to coordinate the stitching procedure. This is the second contribution of this research work. Basic stitching, onion stitching, MCF stitching, and MaxMin stitching are the proposed methods. Simulations results have been presented comparing each stitching method. Regardless of the method, the proposed stitching algorithm outperforms other existing absolute orientation methods. Moreover, among the proposed stitching methods, Basic and Onion stitching perform better than the two other methods, since they use a smaller number of common nodes.

Another map-stitching based algorithm has been proposed by Kwon et al. in [115]. The prime contribution of this research is to prevent flip error in the localization. During the stitching each transformation can be described by three operations: a translation, a rotation, and/or a reflection. *Flip ambiguity* is defined as the minimum stitching errors achievable by reflectional and reflectionless transformations. If a flip graph has both kind of operations, then it is called 'Flip conflict'. In this research, methods for computing the flip ambiguities and for solving the flip conflicts are proposed. For the localization, two patch construction methods have been adopted. MDS and iterative multilateration are the chosen techniques for path construction. Finally, utilizing the information of a reference coordinate system, global coordinates can be computed. Some other anchor free localization algorithms are MDS based Greedy Stitching, Robust Quadrilaterals [42], and Extended Absolute Orientation Transformation [116]. The MDS based and multilateration version of the proposed algorithm perform better than other algorithms in the case of success rate and localization accuracy. A comparative study among the anchor free algorithms discussed above is given in Table 4.

3.3. Future research directions: anchor based methods

We have included several research ideas in this section based on those discussed in the 'Anchor based and anchor free localization' section. Ideas will be discussed mentioning the current research advancement to the best of our knowledge.

3.3.1. Energy efficient localization

Energy efficiency is a primary concern for wireless sensor networks. Very few papers discuss the transmission powers of anchor nodes, which play a vital role in the network localization. More research works are required to relate powers of anchor nodes to the performance of localization, considering some aspects such as mobile anchor nodes, effect of power of anchor nodes in terms of relative position of each anchor node etc.

3.3.2. Estimation of unknown parameters in unknown environments

Literature in localization lacks the discussion on deriving path loss parameters in anonymous environments. [46] represents a recent work on this topic, but this work lacks compact mathematical constraint assumption, and further research is needed to resolve this issue.

3.3.3. State-of-art convex optimization

A lot of recent works have been published on localization that implement convex optimization and SDP [22,49]. It is a good signature of implementation of advanced mathematics that result in competitive, improved, and more accurate localization of source nodes. This flow of implementation can be further continued for implementation of new advancement of SDP and convex optimization. For example, [22] implements nuclear norm approximation in the process of relaxing the objective function, and this research can be extended further by minimization of nuclear norm that may improve the localization accuracy as well as reduce mathematical complexity.

3.3.4. Multiple source localization

Among very few attempts on multiple source localization, some crucial things still need to be considered in the future that are absent in present literature. During localization, uncertainty may arise since source and sensor nodes are not synchronized. Future research on multiple source localization may consider the issue of clock synchronization among the source and sensor node. It may also extend to designing a scheme in which a source can put a signature at the signal that it sends to the sensor nodes.

3.3.5. Anchor free optimization method

Most of the anchor free localization methods implement iterative schemes, but initial assumption in iterative methods may lead to convergence into local minima. Some research works like [18] use optimization method that do not include extensive research on anchor free localization. Prospective researchers can investigate anchor free localization in more detail in order to implement optimization and statistical algorithms.

3.3.6. Security and privacy

Due to the diverse application of sensor networks, security has become a major concern for modern wireless sensor networks. WSNs can be used in warfare, where the enemy can tamper with a sensor by injecting malicious programs. This could cause the sensor to malfunction and provide false position estimation, especially if the victim sensor is a beacon. Then it can compromise the trust and overall integrity of localization of the sensor networks.

Table 4
Comparison among "Anchor Free" localization algorithms.

Localization algorithm	RM	RC	ND	LM	Sc	NM	Co	LAc
ABC [41]	RSSI	Triang	H	Distri	Y	N	Coop	H
AFL [18]	Acous+Connect	Multilat	M	Distri	Y	N	Coop	M
RODL [42]	TDOA	Trilat	M	Distri	Y	Y	Coop	M
MDS-MAP [112]	Connect	MDS	M	Centra	N	N	Coop	M
MDS-MAP(D) [113]	Connect	MDS	M	Distri	N	N	Coop	M
Map-Stitching [114]	Connect	Multila/MDS	H	Centra	N	N	Coop	H
Patch-and-stitch [115]	Connect	Multila/MDS	H	Centra	Y	N	Coop	M

3.3.7. Localization of non-adjacent nodes

[115] presents an anchor free localization method in which localization has been performed using local information collected by sensor nodes. This algorithm assumes shortest path lengths as distances between non-adjacent nodes. More compact algorithms are required for a better use of non-adjacent nodes that may improve localization accuracy.

3.3.8. Expanding the scope of each node in radio map

Proposed anchor free localization algorithms frequently construct a radio map of the concerned area. Each node communicates with other nodes since local information is the essence of constructing a radio map. Future research can be directed to expanding the scope of each node so that it can communicate with more neighboring nodes.

4. Indoor localization

Recently, the indoor positioning system has been very popular due to its crucial application to the construction industry, logistics industry, healthcare, and other official environments. Compared to outdoor localization, indoor localization is more challenging due to the poor performance of GPS under a roof. In addition, indoor environments are generally crowded and cluttered, which make the distance measurement a difficult task. Furthermore, the mobility of an object has made it more complex. So far, the two most common strategies to localize an object in the indoor environment is based on Received Signal Strength (RSS). These are known as range based and range free, or profiling or fingerprinting. Some other hybrid and new concepts have also been proposed. Most of these algorithms deal with the mobility issue along with consideration of different environmental discontinuity. In the following sections, the RSS based indoor localization schemes and other contemporary improvements and attempts are discussed. Different algorithms have implemented different localization. Among them [117,118] use maximum likelihood estimation, [119,120] use triangulation, [121] uses spectrum analysis, [122] uses curve fitting, [123] uses multilateration, and [14,124,125] use a fingerprinting localization method. Moreover [13] uses a combination of fingerprinting and kernel density estimation for the localization of unknown nodes (Fig. 8).

4.1. RSS based indoor localization

RSS based theoretical or empirical models translate signal strength into distance estimation. Since RSS suffers from some problems like multi-path fading, background interference, and irregular signal propagation, it prunes estimation errors. However, from the economic point of view, it has less communication cost and easy implementation.

RSS measurement using range based methods typically consists of two steps. One is *ranging*, in which RSS measurement is used to calculate the anchor position, and the other is *positioning*, in which an unknown node position is estimated based on the distance measurement. In the *ranging* phase, the distance is usually represented by a PLM, and in the *positioning* phase a lateration algorithm is used to solve the distance equation to find out the location. Several range based indoor localization techniques have been proposed in the past few years. Among them, [126] and [127] are particularly notable.

A recent range based indoor localization is proposed by Tian et al. in [117]. A third-order polynomial based log-distance path-loss model is presented in the research work. The proposed path loss model builds the relationship between path loss of channel propagation and the node distance. It has been shown that proposed model performs better than the two-slope model [128], [129]. All the nodes are classified into three categories: fixed nodes, the one master node, and the unknown node. Fixed nodes send and receive the data packets and then filter the RSSI values using Kalman filter to remove noise from the RSSI values. Filtered values are sent to a computer through a master node. Computation makes a model parameter table based on the received data. To localize an unknown node, such a node sends data packets to fixed nodes. Fixed nodes measure the RSSI values and send them to the computer. A computer searches for the best suitable matches from the table and computes the minimum sum of square of the chosen data. At the final stage, maximum likelihood estimation (MLE) is applied to locate the position of the unknown node. The proposed algorithm is compared to [130], and it has been found that the proposed algorithm shows better accuracy than [130].

In [123], the researchers propose an indoor localization algorithm in which they consider the ToA measurement of ultra wideband (UWB) for the location search. Two separate cases are considered in which the first approach is solely based on detected direct path (DDP) and the second also considers undetected direct path (UDP) to propose distinct methods for localization. Among the different available models of range error [131,132], the first proposed approach adopts [132]. In the proposed method, no error model information (NEMI), a revised version of [132], first calculates some intermediate location estimations for different possible combinations of anchor nodes, and then a final estimate is returned as the combination of intermediate estimates. NEMI discards some anchor combinations, considering the large negative value of estimated error $\hat{\varepsilon}_{n,k}$ in UDP measurements. Conjointly with NEMI, another NEMI method with reduced complexity NEMIRC is presented in order to reduce the complexity of the computation, as some intermediate combinations are discarded even before the final estimation if combination does not satisfy the condition of inclusion. In the second part of this research work, a range error model is adopted from the classical LS technique and from [132] to devise a method with DDP range error. Some basic approaches provided in this work are Naive ML method, a method based on [133], and a ML method with knowledge of DDP/UDP configuration.

A hybrid range based indoor localization approach has been proposed in [121]. This is a Wi-Fi based indoor localization approach that utilizes channel state information (CSI) for fingerprinting. It is inspired by two early proposals [134] and [135], respectively known as fine-grained indoor localization (FILA) and fine-grained indoor fingerprinting system (FIFS). The basic distinction

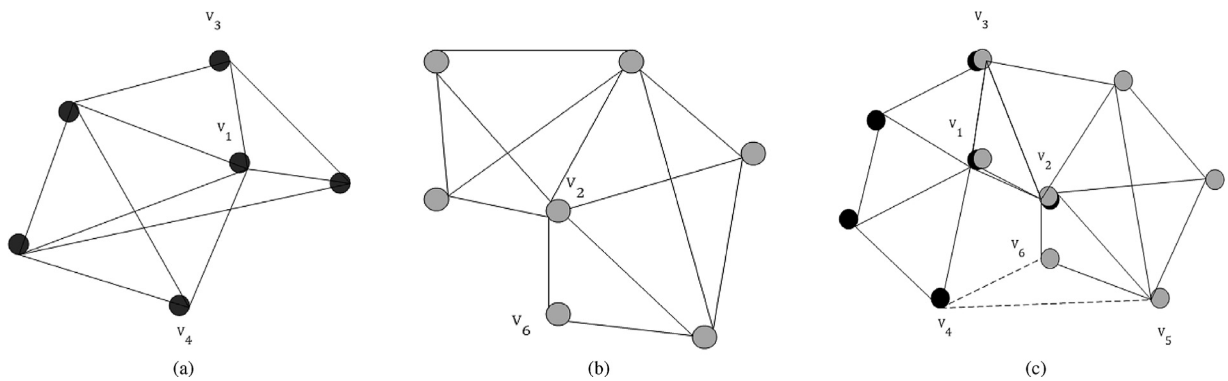


Fig. 8. Rigid map stitching of two local maps (a) and (b) in (c) by overlapping three common nodes V_1, V_2, and V_3.

between these two early proposals and [121] is that in such early versions, two access points are used whereas one access point is used for localization. From this perspective, this algorithm is named as single access point with multiple antennas (FILSAM). As a range measurement technique both ToA and AoA are considered, which are achieved from multiple sub-carriers of an OFDM signal and spatial information of the multiple antennas correspondingly. Before estimating the position of the unknown nodes, several assumptions have been made. For instance, a line of sight (LOS) path exists between the mobile device (MD) and AP, clocks of MD and AP are synchronized, and multiple antennas are calibrated. The whole procedure can be divided into four sections: AoA estimation, ToA estimation, LOS path identification, and finally localization. To estimate AoA, phase difference of multiple antennas are required and the MODE [136] method has been used. The same MODE algorithm is used for the estimation of ToA. When ToA and AoA are estimated separately, the LOS path of ToA (τ_{los}) is calculated based on the assumption that the LOS path is the shortest. Moreover, AoA for LOS path, θ_{los} is estimated by solving an optimization problem. After the calculation of LOS path of both AoA and ToA, localization is straightforward. A mobile device is localized using the following equation:

$$[x, y] = [r_{los}\cos(\theta_{los}), r_{los}\sin(\theta_{los})] \tag{3}$$

where $r_{los} = c * \tau_{los}$ and $c = 3 * 10^8$ m/s is the propagation speed.

4.2. RSS free and profiling/fingerprinting based indoor localization

In the range free based method, or profiling method, the localization is completed in two stages: *profiling* and *estimation*. These two steps are also known as the offline training phase and online estimation phase, respectively. In RSS profiling a radio map is generated to monitor the indoor area by collecting the RSS readings from known locations. Later, at the estimation stage, the location of an unknown node is estimated by exploring the radio map. A lot of research work has been published on this topic. The research works adjoining the recent state-of-art efforts are discussed below.

In [119], a radio-frequency based scheme, RADAR, has been proposed to locate and track objects inside an indoor environment. For experimental purposes, several base stations are set up to use the signal strength information gathered at multiple receiver locations. To calculate the position of a user, both empirical based and theoretically computed signal strength are used. The whole process starts with data collection followed by data processing. In the data processing step, utilizing the processed signal strength information, the number of walls obstructing the direct line between the base stations and the data collection positions are calculated. The data collection phase is coined as the *offline phase*. Data processing is the *real-time phase*. In this phase, the signal strength data are summarized for all base stations and compared with the user location and orientation in two ways: *empirically* and by *signal propagation modeling*. Finally, using nearest neighbor(s) in signal space (NNSS), the deviation between the user locations and the collected data are calculated for multiple locations, and the location best matched to the signal strength is then picked as the user actual coordinate. Simulation results confirm more accurate performance of the *empirical method* and also show that the *signal propagation model* provides cost effective and easy deployment of sensors.

Lionel et al. propose a localization technique termed LANDMARC based on RFID technology in [120]. In this technique, using extra reference points, measurement accuracy is increased. All the RF readings for both reference points and tracking objects are measured. Then the Euclidean distance between unknown points and reference tags are calculated. This is the difference between the signal strength of reference and tracking objects. Every tracking object calculates its distance from nearest neighboring reference points, where distance is defined as that between the power levels of the reference tags and that of tracking object. Three performance impacting major issues are considered in this proposal. The first one is the well placement of the reference points while the second one is consideration of the optimum number of reference points surrounding a tracking object. If k-nearest neighbors are considered, then the unknown tracking objects' coordinate (x, y) is calculated as:

$$(x, y) = \sum_{i=1}^{k} w_i(x_i, y_i) \tag{4}$$

where w_i is the weighting factor of the ith neighboring points. Finally, a third major issue is choice of these weighting factors. If E is the distance, then according to this algorithm the weighing factor is given as:

$$w_j = \frac{1/E_i^2}{\sum_{i=1}^{k} 1/E_i^2} \tag{5}$$

Although this algorithm is simple to implement, it has several other disadvantages. Although this method requires cheap RFID rather than a large number of expensive RFID readers, it suffers from major measurement errors due to variation in behavior of reference tags. Moreover, unavailability of RFID that can provide signal strength information directly is also a major concern. In addition, long latency and measurement errors due to dynamic environments are obstacles to a better accurate position estimation.

In [118], the authors develop a localization algorithms based on compressive sensing for indoor wireless local area network (WLAN) using mobile devices. Formerly, several research attempts have been made on this issue to estimate the position using RSS measurement. Among them [137,138] use the k nearest neighbor (KNN) based positioning scheme along with an indoor radio map.

In [139–141] algorithms implement Compressive Sensing (CS) for the localization. Additionally, in [142] the positioning is done on the access point (AP). The research work presented in [118] propose a different method to measure the distances between the measured RSS values and the radio map. Due to the mobility of numerous mobile devises, it is more challenging and complex to localize an object accurately. Although the position of a mobile can be determined precisely using the Bayesian compressive sensing (BCS), the large number of mobile devices causes localization errors. However, a new term 'error bar' has been introduced as a metric to measure the accuracy of location vectors. The term Adaptive Multi-task BCS (AMBCS) has been used to denote that idea. Furthermore, it is investigated that increasing or decreasing the number of measurements dynamically can improve the localization accuracy and that approach is named greedily adaptive MBCS (GAMBCS). Performance of the MBCS algorithm can degrade with the increment of MD. AMBCS performs with high accuracy even if the number of MDs varies.

A novel curve fitting (CF) based profiling algorithm has been proposed for the indoor localization scheme in [122]. This algorithm can be summarized in two steps. First is separating the whole area into different subareas, forming fingerprints for each subarea and localizing a mobile device to a subarea. In the second step, two location search algorithms are used to find a mobile device's exact location. The whole area is divided into subareas, and fingerprints are created for each subarea for each unknown node. Then CF is conducted for each reference node in which the main objective of CF is to construct an RSS-distance fitting function illustrating the relation between the RSS at some space point and its distance to the transmitter. The next step is to locate a mobile device into a subarea. In order to do this, a mobile's fingerprint is compared with those subareas fingerprints, and the subarea with the minimum fingerprint distance is selected. Then, the search algorithm is conducted to find the location of the mobile device where the sum of distance estimation error J for each reference node is a minimum. Two search algorithms, Exhaustive Location Search (ELS) and Gradient Descent Based Location Search (GLS), are selected as the search algorithms. In ELS, the subarea is divided into grid points, and search is conducted for the grid point where distance estimation error is lowest. On the other hand, in the GLS method, a location with lowest J is found through iterations. To observe the performance of the proposed algorithm relative to others similar algorithms, such as fingerprint-based nearest neighbor algorithm and traditional PM-based (Path Model) algorithm, simulations have been conducted. CF based algorithm is proven to be more accurate than traditional PM based algorithm in terms of the distance estimation. Among the proposed CF based methods, CF-GLS performs best.

Haque et al. present a profiling based algorithm called 'location estimation by minimum oversampled neighborhoods' (LEMON) in [125]. It is a KNN based profiling method that is more flexible than other existing KNN based methods like RADAR [119] and LANDMARC [120] since it uses low cost low power wireless sensors. Two methods are proposed in this research work: LEMON and a combinatorial version of LEMON localization technique. As additional features of [125], a model for Bayesian network and MLE based localization is also discussed. According to the LEMON localization method RSS profiled samples are stored in the database. To find the K nearest neighbor, K closest samples are selected for a query sample keeping the discrepancy between the profiled sample and the query sample lower. Then the estimated location is the weighted average of these K samples. In the combinatorial variant of LEMON, the algorithm produces a combination of K samples out of total stored profiled samples. Then an intermediate estimate is calculated to use in the final weighted estimation. [125] also briefly discusses the possible algorithms for Bayesian networks and MLE estimation.

Another fingerprinting based localization algorithm has been proposed by Wu et al. in [14]. The proposed method Locating in Fingerprinting Space (LiFS) utilizes a user's mobile phones for the localization, which replaces the traditional site survey. This algorithm works in two phases: *training phase* and *operating phase*. The *training phase* starts with forming a stress-free floor plan. An area is represented by a mesh of grids, and a distance matrix is formed where distances between all pairs of locations are included. These distances are the walking distances between each pair location. MDS [63] uses the distance matrix to map all location points into d-dimensional Euclidean space. The Euclidean distance between the two points indicates walking distance between this pair. At the second step of the *training phase*, fingerprinting space is created. To create fingerprinting space, RSS fingerprints for each anchor node at position are stored along with distances between such pairs of positions. The Floyd–Warshall algorithm [96] is used to compute all-pair shortest paths of fingerprints. In the fingerprint space, creation of a stage distance is defined as the number of footsteps between each pair of positions. Distance measurements form another distance matrix, which is taken as an input in MDS to map all positions into d-dimensional space. The last stage of the training phase is mapping. In the mapping step, corridors and rooms are mapped separately while k-means algorithm [143] is used to map the rooms. In the *operating phase* for a location query, an RSS fingerprint is sent by a user, while LiFS searches it in a fingerprint database using a nearest neighbor algorithm. Finally, the best suited matches are considered as the location estimation and sent as the feedback to the user.

Another WLAN based profiling algorithm for indoor localization has been proposed in [13] by Wu et al. An online radio map is generated using kernel density estimation (KDE) [144,145] and a neural-fuzzy-based interpolation method ANFIS [146]. KDE forms a density distribution to depict the RSS-position relationship, which is flexible with NLOS propagation. On the other hand, the deterministic approach ANFIS uses interpolation to generate a radio map from training data pairs. Stochastic radio maps are more realistic as they consider possible dynamic variations in the environment. The novelty of this algorithm is to combine adaptive local search (ALS) with particle filter (PF) to improve the robustness of estimation. It re-samples and corrects the motion uncertainties of a robot by implementing an empirical covariance matrix. ALSPF deals with the problems of particle degeneracy (PD) and infeasible estimate (IE), caused primarily due to environmental noise. PD implies that updating particles whose contribution to the approximation of $p(x_k|z_{1:k})$, where x_k is the position of a robot and z_k is the position measurement of the robot delivered by the sensors at time instant k, which is zero, requires a lot of computational effort. On the other hand, IE refers to prediction of an infeasible region since unpredictable noise disturbs WLAN-RSS, robot velocity, and orientation. A suitable metric to measure the degeneracy of a algorithm is the effective sample size [147]. A base station selection strategy is also applied, which selects the strongest base station with the smallest variance to optimize estimation stability.

In Fig. 9, the ALSPF algorithm is explained showing the important steps, where $\hat{x}$ denotes location estimation and $P(x_k|z_k)$ denotes the weight of a particle. Fig. 9a shows the detection of the IE due to noise, while in Fig. 9b exhaustive search has been done according to the ALS algorithm. In Fig. 9c, surviving particles are shown after the evaluation of new estimate and covariance.

A WLAN (Wireless Local Area Network) based fingerprinting localization method has been proposed by Talvitie et al. in [124]. To construct a proper and more reliable fingerprint database, interpolation and extrapolation methods are used. Interpolation fills the gaps between the collected data points, and extrapolation tries

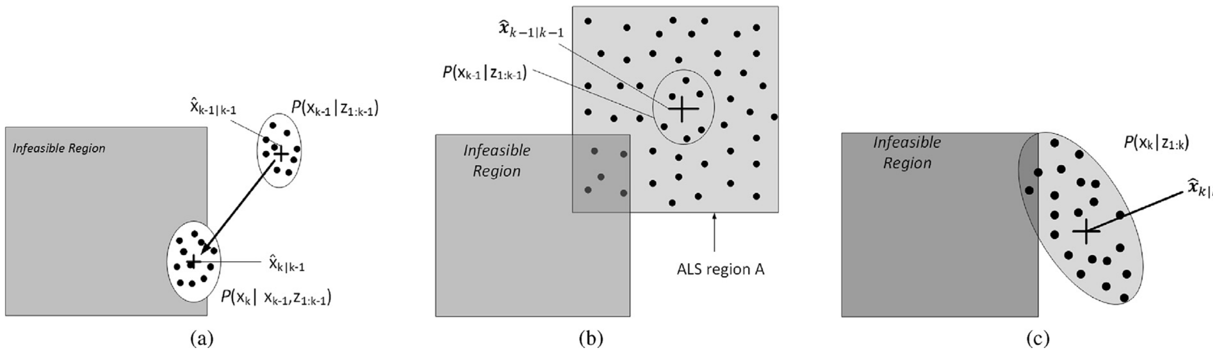


Fig. 9. Illustration of ALS algorithm. (a) Infeasible Estimate (IE) occurs due to unpredictable noise. (b) IE is detected and ALS algorithm is implemented by expanding a reasonable area to search for a better solution. (c) Assessment of a new estimate and covariance by the surviving particles.

Table 5
Comparison among indoor localization algorithms.

Localization algorithm	RM	RC	ND	LM	Sc	NM	Co	LAc
Third-order propagation model [117]	RSSI	MLE	H	Centra	Y	N	NonCoop	M
RADAR [119]	RSSI	Triang	M	Distri	Y	Y	Coop	L
LANDMARC [120]	Power level	KNN	H	Distri	Y	N	Coop	L
NEMI [123]	ToA	Multila	H	Distri	Y	N	NonCoop	M
Adaptive MBCS [118]	RSSI	CS	M	Centra	Y	N	Coop	H
FILSAM [121]	ToA+AoA	Spectrum Analysis	M	Centra	Y	Y	NonCoop	H
CF [122]	RSSI	CF	M	Distri	Y	N	NonCoop	M
LEMON [125]	RSSI	FP	M	Centra	Y	N	NonCoop	H
LiFS [14]	RSSI	FP	M	Distri	Y	Y	Coop	M
ALSPF [13]	RSSI	FP+KDE	L	Distri	Y	Y	NonCoop	H
IEL [124]	RSSI	FP	M	Distri	Y	N	NonCoop	M

to estimate the data outside the known data points. Localization accuracy can be increased by removing fingerprint data from the database. At first, a fingerprint database is formed for both 2.4-GHz and 5-GHz bands. Then, to apply the interpolation and extrapolation, some fingerprint data are removed from the database. Data are removed in large blocks rather than by using a simple probability distribution. Interpolation and extrapolation are applied in both joint and disjoint manners. In the disjoint extrapolation minimum, mean and gradient based methods are used whereas a linear method is used for disjoint interpolation. The gradient based methods are inspired by [148,149]. For the joint interpolation and extrapolation, Nearest Neighbor (NN) and Inverse Distance Weighting (IDW) are used. A Voronio diagram [150] is used for the NN method, and Shepard's algorithm [151,152] is used for IDW. For the final positioning, a probabilistic approach is adopted. Results have been compared with other positioning algorithms like NN and KNN. Table 5 shows the comparison among indoor localization algorithms.

4.3. Future research directions

Research works on indoor localization presented in this section discuss in depth problems of indoor localization and propose some new solutions to those problems. Still, some aspects of indoor localization require proper investigation and demand new techniques to improve the accuracy and practical issues of indoor environment.

4.3.1. Uncalibrated antenna

A multiple antenna based localization based algorithm has been proposed in [121]. This is the most recent research effort on antenna based methods. However, some issues are uncovered. This method shows that 0.5m accuracy is obtained using 4 antennas. Future research work can concentrate on reducing the number of antennae per access point. An antenna can also be uncalibrated, which should be discussed in future works on indoor localization.

4.3.2. Non-LOS path

In indoor environments, due to a large number of walls, obstacles and moving people, the first arrival path between a transmitter and a receiver is rarely LOS. Several research papers can be found on indoor localization that emphasize resolving NLOS path, such as [13,153], and [154]. Due to the page limitations some of these works are not discussed in this survey paper. For example, [13] and [154] include NLOS conditions in mathematical derivation of the proposed schemes rather than negating and discussing its impact on the accuracy of the scheme. Future works can investigate this issue in more detail by considering anchor free NLOS condition in indoor environment. A brief survey dedicated to NLOS condition can be found in [155].

4.3.3. Reducing dependency on anchor nodes

Most of the recent papers on indoor localization depend heavily on anchor nodes. For instance [117] proposes a third order channel propagation model for indoor localization that utilizes at least four anchor nodes. A more advanced scheme is required that will require fewer anchor nodes without reducing localization accuracy.

5. Localization in static and mobile sensor networks

Localization schemes can also be classified into "Static" and "Mobile" localization algorithms. In the tables of preceding sections (e.g.,Table 3 and Table 4), the localization algorithms specify whether they are static or mobile. Very few recent localization algorithms discuss the mobility issue of the sensor nodes. Among them, most of the localization algorithms use the node's mobility information to enhance the performance of proposed algorithms, which eventually yields more accurate position estimation. Since algorithms are already discussed in the previous sections, this section presents a brief discussion on the mobility issue of the localization algorithm, and the contribution of the proposed algorithms to the issue of node's mobility is addressed.

5.1. Static vs. mobile localization

Localization schemes with high accuracy positioning information cannot be implemented by mobile sensors since they usually require centralized processing that takes too much time to run. Centralized schemes also make assumptions about network topology, which is not applicable for mobile wireless sensor networks [25]. Mobility can affect the localization process in many ways. One of the prime concerns regarding mobile sensor network is latency. Longer time taken by localization may cause latency, as the sensor will have changed its position since the measurement took place. Doppler shift is another issue in MWSNs. Doppler shift can occur when the transmitter of a signal is moving relative to the receiver. Moreover, since most of the proposed localization techniques require LOS, the movement of mobile sensor nodes may cause the localization to take place in a degraded LOS position.

S. Salari et al. [12] uses mobility information of the sensor nodes to improve the accuracy of the localization algorithm. In [61], the algorithm uses both fingerprint and accelerometer information for the localization, which is proven to be better than the algorithms, which use only fingerprint or accelerometer information. The algorithm proposed in [59] uses basic directional and meandering mobility models for the localization of moving sensor nodes. On the other hand, the algorithm proposed in [62] uses a random-way-point model for mobile nodes. RODL algorithm in [42] proposes the quick repetition of the algorithm phases along the movement of the mobile nodes for the localization. This algorithm proves that least-squares optimization is better than trilateration for the localization of mobile nodes. In [156], the authors discuss a kinetic sensor based fast robot identification and mapping algorithm. A pedestrian group detection and tracking algorithm has been presented in [157], which develops a novel temporal-spatial method for grouping and an event detection technique for contextual behavior recognition. The proposed algorithm in [119] considers the random walking of the users whose positions are needed to be estimated, and it uses a sliding window of 10 samples to calculate the mean signal strength on a continuous basis. This information is applied in the basic proposed method to localize the mobile nodes. In [14], the algorithm proposes the continuous collection of RSS readings for the localization of mobile nodes. Thus, this algorithm creates a moving trajectory of mobile nodes, and finally, the best fitted trajectory is selected for localization. The particle-filter-based algorithm proposed in [13] uses a mobile robot to evaluate the performance of the algorithm. It measures and stores the RSS data continuously and applies the algorithm to track the position of mobile robots. Almost all of the proposed algorithms adopt similar mobility models, which consider velocity information to design the models.

5.2. Future research directions

A lot of recent works on localization have addressed mobility of sensor nodes, but among them only few consider mobility of both source and sink nodes. Open issues and research challenges in this context are discussed below.

5.2.1. Variable velocity of sensor node

Although a lot of development has been done on static localization of wireless sensor networks, mobility is still one of the less explored aspects of this field. Few papers have dealt with the issue, and some have even used mobility information to improve the accuracy of the estimation of a sensor node's location. Recent papers have used almost similar models to consider the velocity information to estimate the position of a node. Several other mobility models are available in theory, but recent research works neither adopt these mobility models nor compare their performance in terms of localization accuracy. Mobility models adopted by research works like [12] and [61] consider constant velocity between two successive time intervals, which is not always true in real world scenarios. A possible research idea could be the mutual exchange of mobility information among nodes. If a sensor can send relative velocity information to the neighboring sensors, then this type of incorporation may improve the localization accuracy.

5.2.2. Mobile nodes to ensure security

Future research on security issues has already been discussed in the anchor based vs anchor free section. Mobility can be used to ensure security of localization in sensor networks. Mobile nodes can actually be integrated as part of a secure localization. Research can be done in which the position of malicious nodes can be detected by localization of a mobile node placed near malicious nodes.

5.2.3. Anchor free mobile node localization

S. Salari et al. [12] presents an excellent work on mobility issues and considers the mobility of both the anchor nodes and the sensor nodes. However, it would be a challenging task to localize a mobile node without any anchors while ensuring good accuracy.

6. Typical applications of localization

Although wireless sensor networks were first introduced as a technological tool for military use only, it is now being used for many different purposes, including healthcare, weather forecasting, environmental observation, transportation systems, and home and office applications. Since applications of the localization process within a wireless sensor network are a sub-group of the applications of WSNs, only certain cases of applications of sensors in which localization concepts are used are discussed in this paper. The implementation of localization technology of wireless sensor networks in different fields are discussed in the following subsections.

6.1. Military applications

The usage of sensors in military can be divided into four basic categories: battlefield application, infrastructural application, application beyond the battlefield, and force protection. Some good reads are available on military application in [1,2].

In the battlefield, sensors with different measurement techniques are used for different arms technology. Distributed self-contained acoustic position systems and accelerometer sensors provide antitank landmines [158] with sensing information regarding threats from their neighbors states and help to respond. Future technological scenarios of landmines are discussed in [159].

Airborne acoustic sensors are used in aerostat arrays to detect and calculate the positions of transient signals from mortar, artillery, and small arms fire while ground acoustic sensors are used to localize the source [160]. Also, to detect and localize battery operated modern submarines, low cost passive and active acoustic sensors are used [161].

To detect hazardous chemicals, low-cost chemical sensors are deployed in an unmanned aerial vehicle. To avoid false alarm, the sensors are fused with three color filtered photo-diode detectors, which can distinguish terrain variation due to different chemical emissions [162].

To secure the military infrastructure from enemy attack, sonar and seismic sensors are deployed to detect enemy soldiers approaching. In this security system, only the images matched with the sonar sensors are transmitted.

Acoustic localization is performed to protect soldiers from sniper attack. Two acoustic arrays and a day/night video camera

Table 6
Summary of comparisons among IoT communication systems [171].

System	Sensing	Communication	Range (m)	Power
RFID	No	Asymmetric	10	Harvested
WSN	Yes	Peer-to-Peer	100	Battery
RSN	Yes	Asymmetric	3	Harvested

mounted on the soldier's helmet are used to localize the source of the shooter [163–165].

6.2. Emergency service applications

One of the most vital civil applications for a wireless sensor network is its role in emergency services, such as police, fire, and medical via 911 calling. One such implementation involves the localization of a mobile station placed within a city for citizens to place immediate 911 calls [15]. Location estimation is done using at least two anchor nodes serving as base stations [15]. In addition to general purpose emergency response management, WSN localization can also be used in management of specific emergencies. Most notable examples include detection of a specific phenomenon such as a landslide [166] as well as detection of survivors of a given natural disaster [167]. These particular scenarios can be perceived as the acquisition of intelligence with which emergency personnel can respond to aforementioned events with optimal speed and preparedness.

In order to further enhance smart decision making from the end of such personnel, WSNs can be utilized in the simulation of hazards, such as a fire [168]. In this example, WSN localization is used to sense the spread of a fire or other danger within a building while an external simulator provides input to the sensor nodes [168]. Fire prevention by means of wireless sensor networks is also addressed more directly with solutions available for localization and communication within an affected urban or industrial environment [169]. A similar scenario is also addressed for early, preemptive fire detection in both outdoor and indoor public environments [15].

6.3. Internet of things (IoT) and cyber physical systems

The Internet of things (IoT) and cyber physical systems are newly emerging applications in which localization of sensors has an important role when a wide plethora of electronic devices communicate with each other and control the systems. For example, we are already familiar with receiving internet access on a personal computer and, more recently, from a tablet and smartphone. Other common household devices, however, are also becoming subject to internet accessibility, including televisions, game consoles, watches, and even refrigerators. As more devices follow the trend of representing smart objects [170], the importance and potential of interfacing devices with one another become of increasingly great importance. This novel method of inter-device interaction is fueled by a combination of multiple potential communications protocols, including radio frequency identification (RFID) and near field communications (NFC).

Wireless sensor networks, on the other hand, are an equal if not greater method of data communication, due to the continuous need for localization and tracking [172]. A brief comparison of WSNs, RFID systems, and RFID sensor networks are provided in Table 6. In short, the table infers that RFID-based options are of low cost and small size with a long, battery-independent lifetime while WSNs are purely peer-to-peer and do not require a reader [171]. As a result of such a less centralized approach and greater feasible range, localization of an IoT-based smart object is most effective when implemented as a WSN.

6.4. Health care applications

Recently lots of sensor based applications are developed to serve complex medical purposes. To monitor the physical condition, a body area network (BAN), has been developed, which detects different physiological aberration of a human body and transports the collected data to a central node. Lately, sensors are used to calculate the possibility of a future medical emergency along with updated physical conditions. Almost all of the recent medical technical devices like Ubimon [173], E-watch [4], CodeBlue [5,6], Vital Sign Monitoring System [174], MobiHealth [3], Multi-Electrophysiological system [175], and Life-shirt [176] have adopted sensor based networking, which audits the current physical condition of a human body, detects abnormal behavior, and transfers the data for emergency medical care. Wireless sensor networks are also employed in glucose level monitoring, cancer detection, monitoring of cardiovascular diseases, asthma, heart rate, and more. Localization works as a part of many of these applications. Implementation of localization schemes in some applications are discussed as follows:

Localization is also used to monitor the movement of elderly people and detect abnormal movement that may be caused by Alzheimer's, a disease frequently suffered by the elderly. In [177], to detect abnormal movements that may result to seizures, an accelerometer based scheme has been proposed. According to this algorithm, daily activities of an elderly person are observed using ZigBee protocol devices. On the other hand, researchers in [178] devise a method based on mobile phones and a wireless sensor network using Bluetooth or ZigBee for monitoring.

After hip surgery, a patient's leg position is constantly monitored by a system [179]. If this position calculation is found to be incorrect, it will send a alarm to the control unit.

6.5. Traffic monitoring applications

One of the most popular applications of sensor networks is the transport control and monitoring system, where localization has became a integral part of modern vehicular technology. Intelligent transport system (ITS) adopts sensor technology for traffic management and safety as well as to build an ideal city with astute traffic control mechanisms [180]. The typical applications of wireless sensor networks in ITS include traffic light control, parking space management, and traffic optimization through reduction of a driver's travel time by providing information about re-routing and changing lanes.

The vehicular technology localization concept is currently being used to improve driver's safety. In a proposed scheme, traffic information incorporates with a data center to help avoid traffic accidents by implementing both on-road nodes and an ad-hoc infrastructure system [16]. Some schemes use magnetic sensors as well as wireless signal strength and quality to detect approaching vehicles. These information, together with on-road nodes, help to ensure a secure transport system [181]. Another traffic control mechanism [182,183] improves vehicle security, gathering information about harsh environments like forests and icy areas along with regular road nodes. To detect a traffic jam, a vehicle's position, with respect to other nearby vehicles to ensure unwanted accidents while route changing, can help a driver to reduce the travel time and eventually can pave the way for a smart traffic system.

6.6. Environmental observation and weather forecasting applications

One of the most important application of a wireless sensor network is environment monitoring and weather forecasting. The applications of a sensor network in the field of weather monitoring and weather forecasting include habitat monitoring, agricultural issues, forest and water quality monitoring etc. Being an imperative part of some of these applications, different localization algorithms ensure proper position estimation. Localization is applied in cattle monitoring, since research has shown that anthropogenic effects have been observed among plant and animal behavior due to someone's physical presence being in front of them [184,185]. This kind of animal tracking can ensure reliable data collection without disturbing the ecosystem. Localization is also used to observe the effect of earthquakes on different building components [7]. It investigates how a building responses to different vibrations caused by earthquakes at different distances.

To determine the ecosystem of different places, the localization concept is used at sensors. It helps to construct a map that represents the ecosystem distribution of a certain area [17]. Another way of forecasting a disaster is to place various geographical sensors, like wireless probes (WP), at different locations to monitor and alarm about natural disasters. WPs consist of a deep earth probe (DEP) and of sensors placed outside and inside a DEP to monitor and detect landslides [10].

6.7. Home and office applications

Wireless sensor networks have improved the home and office environment by exploiting the sensor technology to reduce the energy consumption in indoor environments. In indoor applications, localization is essential. In this paper, a separate section has been dedicated for the study of indoor localization algorithms. 'Smart Kindergarten' [186] is a project that implements sensor technology to build a smart infrastructure for a kindergarten. This mechanism will observe a child's activities in the kindergarten school by location estimation and deploying embedded modules, integrated toys, and mutual wireless communication among toys to provide feedback about the development of children.

Several other projects [8,9] have been proposed that ensure proper energy consumption in indoor environments. In the vision-based user-centric light control mechanism, localization is used to calculate a person's presence and activity in a room to determine the light control mechanism, which consequently improves the energy use of lights.

7. Conclusion

In this survey, we have explored state-of-the-art research results and algorithms proposed for localization in wireless sensor networks. We have presented the recent advances on localization techniques in WSNs by considering a wide variety of factors and categorizing them in terms of data processing (centralized vs. distributed), transmission range (range free vs. range based), mobility (static vs. mobile), operating environments (indoor vs. outdoor), node density (sparse vs. dense), routing, algorithms, etc. A side-by-side comparison summary in a tabular form for different localization algorithms in WSNs is also presented. Although there has been significant research in other aspects of WSN, more research in localization issues is necessary to offer accurate location-based services in future wireless systems. There will be no single method that can help to find exact location of nodes in the entire wireless networks. To handle a variety of scenarios, implementation of a combination of techniques as well as of context-based techniques would be needed to estimate accurate location in future wireless sensor networks.

From the comparative analysis of the localization algorithms, we can form conclusive remarks regarding the localization algorithms. In different scenarios, different noise distributions have been considered while observing their performances. While the range based algorithms show promising performance, their related hardware cost sometimes makes such schemes less preferable than range free algorithms. Application of optimization theory and the addition of mobility information show promising improvement in the localization accuracy. Although most of the centralized algorithms are proven to be better in performance, distributed algorithms give better results when sparsity of the network structures is considered. Thus, the choice of localization algorithms depends primarily on specific application scenarios.

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