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A survey on sensor localization

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Abstract: Localization is one of the fundamental problems in wireless sensor networks (WSNs), since locations of the sensor nodes are critical to both network operations and most application level tasks. Although the GPS based localization schemes can be used to determine node locations within a few meters, the cost of GPS devices and non-availability of GPS signals in confined environments prevent their use in large scale sensor networks. There exists an extensive body of research that aims at obtaining locations as well as spatial relations of nodes in WSNs without requiring specialized hardware and/or employing only a limited number of anchors that are aware of their own locations. In this paper, we present a comprehensive survey on sensor localization in WSNs covering motivations, problem formulations, solution approaches and performance summary. Future research issues will also be discussed.

Keywords: Sensor localization; Wireless sensor networks; Range measurements; Anchors; Mobile sensor; Probabilistic localization

1 Introduction

Wireless sensor networks (WSNs) have numerous applications that include object tracking, traffic monitoring, habitat monitoring, measuring radiation levels from nuclear reactors, detecting seismic activities, navigating ships, and so on. Recently, researchers have also started exploring smart applications in the domain of pervasive computing by leveraging embedded processing with WSNs. In all these applications, sensor node locations are critical not only to the application's goals but also to the operations of WSNs.

In this paper, we attempt to present a comprehensive survey on the state-of-the-art research concerning localization of nodes in WSNs from motivations to solutions. Our focus, therefore, is on WSNs that apply protocols and algorithms with the underlying assumption that node locations are known. We motivate the readers by identifying the basic problems in deployment, data gathering, and optimal resource usages; and thereby examine how localization becomes critical to the applications of WSNs.

An important problem in the deployment of WSNs is the coverage. A coverage model of sensor nodes would depend on the distance between the point of interest and the closest node. Therefore, locations of sensor nodes constitute the basic input for the algorithms that examine coverage of the network [1].

Location-based routing (LR) protocols are based on the location information of sensor nodes. The advantages of LR protocols include better scalability and less overhead caused by dynamic changes in topology [2]. Moreover, location-aided routing (LAR) utlizes location information to obtain a much smaller request zone than the potential searching area for routing paths. A recent study [3] indicates that even with the help of a simple anchor-free localization algorithm, the LAR protocol performs as competitively as the shortest path routing algorithm under ideal assumptions. Besides, geographic addressing uses the physical locations of nodes as global references to facilitate identification and communication within a network.

Beyond the networking protocols, most applications involving WSNs use location information to interpret the meaning of sensory data from different regions. For instance, location information constitutes an essential ingredient for reasoning about contexts [4], especially in smart environments.

There exist well organized surveys on sensor localization in the literature [5∼7]. Most of these works report either early results on sensor localization, or on location methods having origins in cellular networks or robotics. The focus of this paper is an up-to-date comprehensive survey on localization of sensor nodes in a WSN. Unless stated otherwise, throughout the paper the term "localization" will mean sensor localization.

The paper has been organized into six sections. Section 2 gives a taxonomy of localization schemes and formulates the localization problem in multiple ways. Section 3 deals with the algorithmic frameworks behind some of these solution approaches. Section 4 provides a performance comparison on the efficacies of these localization schemes in terms of their accuracies and costs. Section 5 briefly discusses open issues and future research directions. Finally, Section 6 concludes the paper.

2 Taxonomy overview and problem formulation

The problem of sensor localization is to determine the location information of all or a subset of sensor nodes, given the measurements of pairwise spatial relationships between the nodes. Here, location information means any form of

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location indicator such as exact location, the deployment region or the location distribution, while the measurements on spatial relationship could be on the proximity (nearness), the distance or the angle between nodes. A taxonomy of the sensor localization problem is shown in Fig.1 according to various combinations of inputs and objectives.

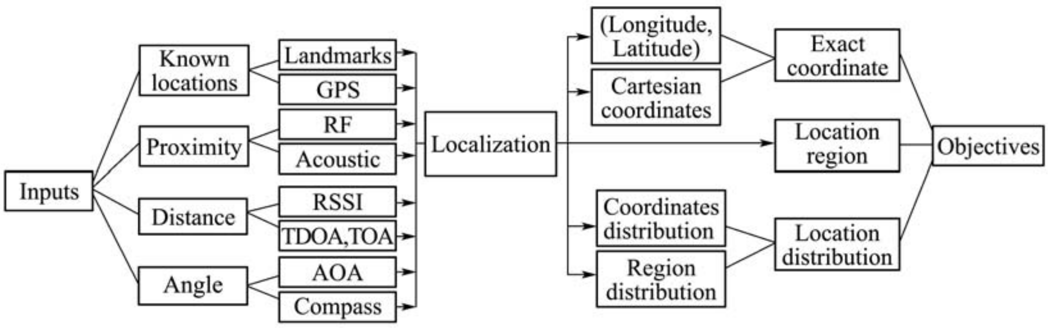

Fig. 1 Problem overview.

The nodes that are aware of their own locations are either placed at fixed points or equipped with global positioning system (GPS) devices. They serve as references to the other nodes that are to be localized. In order to eliminate the inherent problem of low accuracy in proximity based localization, additional measurements on distance, angle or both are used. Distance measurements can be obtained by utilizing the received signal strength indicator (RSSI), time of arrival (TOA), time difference of arrival (TDOA), etc., while angle measurements rely on compasses or special antennas [8].

In the absence of reference nodes, localization methods focus on forming a map of nodes with respect to a standalone coordinate system [9]. Knowing relative locations is sufficient for certain applications. However, given the absolute locations for a subset of nodes, relative locations can be transformed into absolute ones.

The use of mobile reference nodes in localization is advantageous, because it provides additional measurements on spatial relationships along their corresponding trajectories. However, a mobile reference node, with relatively more resources than an ordinary sensor node, is expensive. Therefore, only a small number of mobile reference nodes can realistically be used for localization. Yet mobile assisted localization exhibits significant improvement over localization methods employing static reference nodes [10].

Despite of range uncertainties and randomness in movements of nodes, probabilistic methods manage to produce good localization results on the distribution of the coordinates or the probability of the presence of the nodes in certain regions [11].

Localization schemes can also be characterized by a set of feature pairs. The schemes differ from one another in the way the inputs are collected. The nodes could be static or mobile, deployed indoor or outdoor, in a 2-D or a 3-D space. Location measurements may or may not require additional hardware. The use of additional hardware in a node should be avoided, as it not only raises the cost, but increases both form factor and operational resource requirements.

Another way to classify a localization process could be on-demand or periodic. A sensor node may take an active role in determining its locations, or it may wait for computation of location information by other devices. Furthermore, a localization process may be centralized or distributed according to the nature of the underlying algorithm.

Finally, the objectives of a localization process varies from absolute to relative locations. Relative locations, which involve virtual coordinates, are adequate for certain applications. Depending on the application's requirements, either coarse- or fine-grain location information may also suffice.

2.1 Localization problems

We categorize the localization problems into three groups: proximity-based localization, range-based localization, and angle-based localization.

2.1.1 Proximity-based localization

The proximity based localization problem can be formulated in terms of a graph model. A WSN is represented as a graph $G(V, E)$. A subset of nodes, $H \subset V$, are aware of their own locations $(p_1, p_2, \cdots, p_m)$. The proximity measurements are typically interpreted using two models: i) the adjacency matrix, and ii) the distance matrix. The goal is to estimate the locations $(s_1, s_2, \cdots, s_{n-m})$ of the remaining set of nodes V-H. An example of sensor localization with proximity information is shown in Fig.2. Different sensors may have different number of reference nodes in their proximity. The accuracy of location estimations increases as a function of the number of reference nodes in the neighborhood.

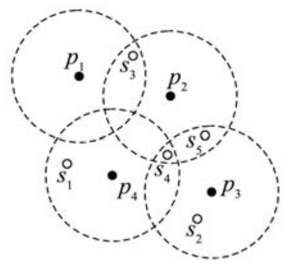

Fig. 2 Example of sensor localization with proximity information.

2.1.2 Range-based localization

The ability to measure the range of wireless signal transmissions is the key to range-based schemes. The prerequisite of range-based methods is to understand different ranging techniques such as RSSI, TOA and TDOA.

Since the nodes are equipped with radios to perform communications, the distance estimation based on received signal strength has attracted enough attention. However, RSSI based range measurements suffer from noise and link reliability. Efforts were expended to obtain the mapping between RSSI measurements and the associated distances to capture the impact of multipath fading and environmental variations on RSSI measurements in the indoor space [12]. Probabilistic model of RSSI range measurements was also introduced to address the uncertainties and irregularities of the radio communication patterns. For instance, a log-normal model was adopted in [13], which assumes that a particular RSSI value can be mapped to a log-normal distribution of the distance between the two nodes, as in equation (1).

$$RSSI \longrightarrow \log d \sim N(\mu, \sigma), \qquad (1)$$

where d is the distance between the nodes, and $N(\mu, \sigma)$ is a normal distribution with mean μ and standard deviation σ.

Another common method for range measurement is based on the time difference of arrivals (TDOA). The signal could be radio frequency (RF), acoustic or ultrasound. An example of utilizing TDOA was introduced in [14], where radio signal and ultrasound pulses were sent simultaneously. Given the time difference of the arrivals, the distance between the sender and the receiver can be obtained by multiplying the time difference by the speed of the ultrasound signal. Similarly, ranging techniques based on time of arrival (TOA), which relies on capturing the signal's time of flight, obtain the distance through multiplying the time of flight by the speed of the signal [15]. The major challenge facing TOA based techniques is the difficulty of accurately measuring the time of flight, since the propagation speed could be extremely high compared to the distance to be measured.

Although computing distances between each pair of locations is trivial, the inverse problem of finding the node locations given the pairwise Euclidean distances is far from trivial. The latter can be formulated as a graph realization problem that maps the nodes in the graph to the points in an Euclidean plane so that the Euclidean distances between nodes equal the respective edge weights. One basic difficulty in the graph realization problem is the non-rigidity of the graph. Given a set of nodes, and Euclidean distances between node pairs as illustrated in Fig.3(a) and (b), the locations of nodes may not be unique. An example of a rigid graph is provided in Fig.3(c), where the nodes get uniquely localized given the distances. More discussions on graph rigidity and network localization can be found in [16]. The study in [17] proved that localization with distance information in sparse networks is NP-hard, while localization with distances of $\Omega(n^2)$ pairs of nodes can be solved in polynomial time, where n is the number of nodes in the network.

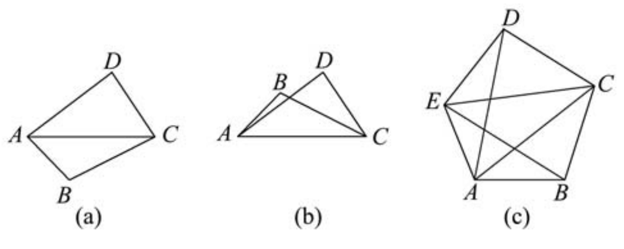

Fig. 3 Graph rigidity.

2.1.3 Angle-based localization

Angle-based localization helps the localization process with additional angle measurements. However, the cost of applying angle measurement is remarkably high due to the requirement of antenna array or multiple receivers on nodes.

With the help of an antenna array, it is possible for the nodes to measure the signal's angle of arrival (AOA) [18]. Alternatively, the angles between different edges of the connectivity graph can be obtained using multiple ultrasound receivers [19]. The angle measurement indicates either the angles to the neighboring nodes or to a certain axis, which provides additional support to the localization or even enables the nodes to be localized solely on the angle information [20].

The difficulty of pure angle based localization has been studied in [21]. Fortunately, the angle information can be combined with the knowledge of proximity. More precisely, it is possible to transform the proximity based localization problem from NP-hard to polynomial time complexity with the knowledge of angle information between all pairs of edges in the network. Therefore, the AOA technique remains an attractive option for localization applications despite of its cost and difficulty in deployment.

3 Solution approaches

Five different localization techniques are discussed in the following from the standpoint of algorithmic solutions.

3.1 Localization with proximity information

The basic idea behind proximity based localization is to approximate node locations with as much accuracy as possible without additional hardware costs.

3.1.1 Anchor-based approaches

Anchor nodes (aka reference nodes, beacon nodes, landmarks) are either deployed at known locations or equipped with GPS devices. They feed their locations to the localization process which propagates these to non-anchor nodes according to the pairwise spatial relationships either between the anchor and non-anchor nodes, or between a pair of non-anchor nodes.

The simplest possible anchor based localization is known as the Centroid method [22]. It approximates the location of a node by the centroid of the anchor locations within its proximity. The accuracy of the Centroid method relies heavily on the density of anchors. To tackle the problem of low anchor density, modified centroid methods have been proposed to allow anchors residing 2-3 hops away to be involved in the localization of non-anchor nodes. However, this leads to the propagation of localization errors along with the location information. A weighted centroid method was introduced to reduce error propagation [23] by assigning different weights to the localized nodes on the basis of densities of anchors in their vicinities. It assists in counterbalancing the accumulation of location errors.

To avoid accumulation of location errors in propagating location information, the Approximate PIT (APIT) test [24] manages to infer the location of a non-anchor node from the region it could possibly reside in. Each non-anchor node runs the Point in Triangle (PIT) tests to find the triangle regions it resides in. However, it is hard for the non-anchor nodes to perform the exact PIT test. The authors presented an approximate PIT test, in which the node is only required to be able to determine if any one of its neighbors is farther or closer to all the three anchors that form its residing triangle. For better localization accuracy, the suggested degree of connectivity should be greater than six.

Considering the impact of anchor nodes on the performance of proximity-based localization schemes, intentional deployment of anchor nodes was exploited in [25]. As shown in Fig.4, the plane is divided into location regions according to overlaps between sensing areas of the anchors. The anchor node located at p_0 sends out beacons of the type $\{A, B, C\}$, and the centroid of the location regions $\{A_1, B_1, \cdots, B_6, C_1, \cdots, C_6\}$ which defines the overlapping regions of the anchor nodes located at $\{p_0, p_1, \cdots, p_6\}$. On receipt of beacons from multiple anchors, a non-anchor node extracts the overlapping regions of the anchors and estimates the centroid of the overlapping regions as its own location. Unlike the Centroid and the APIT schemes, the cell overlapping approach does not accumulate errors in propagating the locations of anchors, nor request RSSI readings for determining the residing regions.

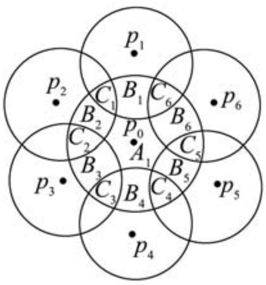

Fig. 4 Deployment of anchors.

To deal with low density of anchors, Gradient [26] and DV-hop [27] methods localize the nodes with the help of the radio range in addition to the proximity measurement. The Gradient method estimates the distance between a pair of anchor and non-anchor nodes by multiplying the hop count of the non-anchor node with the radio range. After approximating the distances to at least three anchors, a non-anchor node applies multilateration to find its own location. In contrast, the DV-hop method computes the average hop distance as anchors exchange their locations and the pairwise hop counts. DV-hop also applies triangulation to localize the non-anchor nodes after obtaining their distances to the anchors.

3.1.2 Anchor-free approaches

The objective of anchor-free approaches is to find the relative locations of nodes from a set of geometric constraints extracted from proximity measurements. Mullti-dimensional scaling (MDS) has been adopted for localization to obtain the approximates on the coordinates of the nodes given the proximity measurements and the radio range. As explained in MDS-MAP [28], the MDS based approach includes three steps. The first step is to form the distance matrix with distances between all pairs of nodes in the network. In the absence of anchors, the distance is obtained by multiplying the hop count with the radio range. In the second step, Singular Vector Decomposition (SVD) is performed to get an initial relative map of the nodes on the plane. The last step performs the necessary flip, rotation and scaling according to the distances between anchors whenever applicable. Otherwise, the relative map would be the result of SVD. The time complexities of the first two steps are $O(n^3)$, where n is the number of nodes in the network, while the complexity of the last step depends on the network topology.

3.2 Localization with range information

The range based localization may or may not require anchor nodes as described below.

3.2.1 Anchor-based approaches

Multilateration can be applied to obtain exact coordinates of a non-anchor node, given at least three anchors in the non-anchor node's proximity and the pairwise range measurements between an anchor and the non-anchor node. For instance, suppose coordinates of m anchors are available, and that the distances between nodes can be obtained through ranging techniques. Let d_{ij} denote the distance measurement between the ith anchor and the jth non-anchor node. The multilateration problem concerning localization is then formulated as follows:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{2}$$

The estimation error, E_j, of the jth non-anchor node is given by

$$E_j = \sum_{i=1}^{m} (d_{ij} - \hat{d}_{ij})^2, \tag{3}$$

where $\hat{d}_{ij}$ is the estimated distance obtained by substituting the coordinates of the jth node with the estimated coordinates in equation (2). Gradient descent can be applied to obtain the coordinates of the jth node achieving the least squared error.

Low density of anchors poses a challenge to the multilateration approach. In order to apply multilateration, DV-distance [9] follows the approach similar to DV-hop [27]. The distances of each hop are summed up to approximate the distance between a non-anchor node and an anchor node that is multiple hops away. The approximated distance is then used in the localization process. One possible variation could be to use the Euclidean distance instead of the multihop distance. The Euclidean distance can be computed from geometric relationships and the single hop distances. An example of multihop localization is demonstrated in Fig.5. According to DV-distance, the distance between the non-anchor node A and the anchor node C can be approximated to be $d_{AB} + d_{BC}$ or $d_{AD} + d_{CD}$ depending on a certain voting mechanism or other criteria. In contrast, the Euclidean method manages to obtain the multihop distance d_{AC} by exploiting the geometric property of the quadrilateral $ABCD$. Given the set of single hop distances, the position of node A is not unique. As shown in Fig.5, A' leads to the same range measurements as A. Therefore, additional neighbors and the corresponding range measurements are needed to eliminate the false estimation. According to the study in [29], "an average of 11-12 degree of nodes in the ranging neighborhood" is required to get 90% of the network to be localized with a localization error of 5%.

Although the semi-definite programming (SDP) approach presented in [30] can be modified to incorporate the range measurements in the localization process by replacing the approximated distances with the measured distances, it tends to produce large localization error when the anchors are placed in the perimeter of the area. A different SDP problem is formulated in [31] to improve the localization performance by relaxing the constraint from equality to inequality. To guarantee that the solution to the transformed SDP is indeed the solution to the original problem, accurate distance measurements of $\frac{n}{2}(n+5)$ pairs of nodes are required. The computation complexity of SDP is $O(n^3)$. Since it is expensive to apply the SDP method in the centralized localization process, a distributed SDP method was presented accordingly to address the scalability issue.

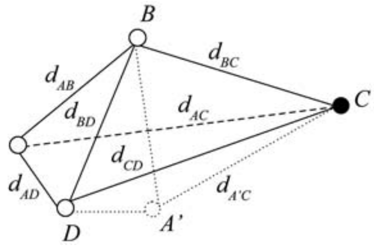

Fig. 5 Multihop localization.

While simple MDS was proposed for localization with proximity information, modified MDS methods were proposed to localize neighboring nodes with range measurements. An iterative MDS approach was presented in [32] to deal with the absence of some pairwise distances. It differs from the classical MDS approach by introducing weights w_{ij} in the objective function. The weights corresponding to the missing pair-wise range measurements are set to zero, while the rest of weights are set to one.

3.2.2 Anchor-free approaches

With the help of a certain number of range measurements, non-anchor nodes could get localized relative to one another through multilateration. DV-coordinates discussed in [9] exploit the above idea through a two-stage localization scheme. During the first stage, neighboring nodes establish a local coordinate system according to the range measurements. The nodes then transform their local coordinates into a global coordinate system in the second stage through registration with neighbors. Because of the insufficient or false overlapping between neighboring nodes, the performance of DV-coordinates suffers from error propagation in the second stage.

The idea of DV-coordinates was explored further in [33]. It leads to the adoption of robust quad, which is the foundation of the local coordinate system for avoiding flip ambiguity. First, the clusters consisting of overlapping robust quads are formed to establish the local coordinate system. The rigidity of the robust quad guarantees that two robust quads sharing three vertices form a rigid subgraph with five vertices. Therefore, the rigidity of the clusters is maintained by induction. Then, to mitigate the impact of noisy range measurements, a threshold on the minimum angle of the robust quad was introduced. With all these efforts on reducing error propagation, the robust quad scheme significantly reduces the location error compared with the other similar approaches.

Triangulation, as proposed in [34], is able to set up a local coordinate system with three nodes and their pairwise distances. Similarly, any node can transform its locations to the coordinate system of its neighbor with the knowledge of the locations in the two coordinate systems and the pairwise distances. Accordingly, the nodes in the rest of the network can calculate their locations with respect to one particular local coordinate system. However, the propagation of one particular coordinate system involves high cost of collaboration among the nodes, which is clearly unfavorable for energy starved WSNs.

3.3 Localization with angle information

If the nodes are enabled with AOA capability, localization can be achieved through multilateration by transforming the AOA measurements to multilateration equations. As shown in Fig.6, anchors A, B and C are the ith triplet of anchor nodes in node S's vicinity. Node S observes the angles $\angle BSC$ and $\angle ASC$. Given the AOA measurements, a trilateration equation can be formed according to the possible locations of node S. As shown in equation (4), S is located along arc $\widehat{AB}$ centered at (x_{O_i}, y_{O_i}) with radius r_i.

$$(x_S - x_{O_i})^2 + (y_S - y_{O_i})^2 = r_i^2. \tag{4}$$

Upon obtaining a number of equations, the non-anchor node can be localized through multilateration.

Regarding multihop localization based on AOA measurements, the node performs induction on the orientation for its neighbors in order to compute one non-anchor node's orientation for an anchor that is multiple hops away. Therefore, the non-anchor nodes can be localized through multilateration after a sufficient number of equations are built.

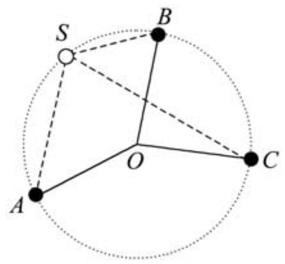

Fig. 6 Localization with AOA.

3.4 Node mobility and localization

Mobility of sensor nodes has double impact on the localization process. On one hand, the uncertainty of node movements leads to increased difficulty of localization. While on the other hand, mobile anchors provide additional measurements to the mobility-assisted localization schemes. Mobility-assisted localization relieves WSNs from the significant cost of deploying GPS receivers and the pressure of provisioning energy for interacting with each other in the localization process.

Statistical approaches having capabilities to handle uncertainty of node movements, can obviously tackle localization of mobile sensor nodes. Monte Carlo localization (MCL) method was adopted in [35] to solve the localization problem in a mobile sensor network. The simultaneous localization and tracking scheme based on Laplace method (LaSLAT) [36] employs Bayesian filters to accomplish the task of localizing mobile nodes, in which location estimates are iteratively updated given batches of new measurements. Extensive empirical studies have shown that LaSLAT can tolerate noisy range measurements and achieve satisfactory location accuracy.

A scheme exploiting the mobile anchors [10] proposed the localization of static sensors using one mobile anchor equipped with GPS. As shown in Fig.7, the mobile anchor periodically broadcasts beacon packets containing its coordinates while traversing the area where static sensor nodes are deployed. Upon receiving the beacon packets, a static sensor determines its location relative to the anchor according to the received signal strength (RSS) of the beacon packet through Bayesian inference.

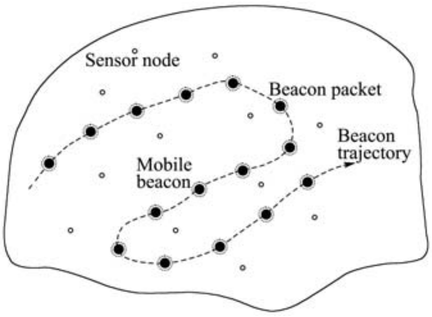

Fig. 7 Localization using a mobile beacon.

A novel idea proposed in [37] was to use extended Kalman filter (EKF) instead of the non-parametric belief model, which is a generalized form of particle filters. The localization is assisted by a mobile robot, which is localized simultaneously with the static nodes. Both the nodes and the robot run EKF to update the location estimation upon receiving RSSI information from anchors and the other localized nodes. They also broadcast the updated location estimations to the neighboring nodes for the next round of update on the location estimation. The mobile robot is led to the less localized area to provide more message exchanges during its visit.

Another novel approach for localization of ground sensor proposed in [38] relies on the use of an Unmanned Aerial Vehicle that receives its location coordinates either from an on-board GPS receiver or from a ground control station. Both relative and absolute locations of the ground sensor nodes can be accomplished by formulating a minimization problem of the virtual potential field force which implies least-square-errors in the results. The optimality of the location estimates is guaranteed by the Lyapunov theory. The proposed algorithm is able to deal with the scenarios when the divergence of the extended Kalman Filter is caused by the first order linearization of the non-linear system.

3.5 Probabilistic approaches

Probabilistic approaches are ideal for handling noisy measurements in indoor localization scenarios where RSSI measurements suffer from severe multipath effects. Two distinct tracks are pursued in probabilistic approaches. One relies on mappings between the RSSI measurements and the locations, while the other manages to capture the statistical relationship between the RSSI measurements and the distances. Both can work with off-line recording and on-line measurements in localizing the nodes with RSSI capability.

RADAR [39] provides a method for mapping the RSSI profile in a space. It consists of two stages. During the first stage, RSSI values from multiple base stations (acting as anchors) are recorded at various locations. A three-step localization process is then performed in the second stage. In the first step, the object's location in the signal space is represented by the sample mean of the multiple RSSI measurements corresponding to the base station. In the second step, an RSSI map of the space is generated from either the empirical data or the propagation model akin to the empirical data. In the final step, the sample mean of the RSSI values from the base station is matched with its nearest neighbor in the signal space.

The major difficulty of implementing RADAR comes from the off-line recording of the RSSI from the base stations. In order to relieve the system from cumbersome off-line preparation, a kernel based learning method was proposed in [40]. The localization problem is formulated as a pattern recognition problem with its kernel matrix being the signal strength matrix. The method requires training data for the learning process. However, the training data can be obtained through automated signal collecting phase. The pattern recognition algorithm focuses on determining the regions that each node resides in. The centroid of the intersection region, which a node belongs to, is regarded as its location. Though the localization process of the kernel-based learning method can be performed locally, its training process is inevitably centralized and computation extensive. A fully distributed localization method without explicit statistical model for range measurement was presented in [41]. Locations of nodes are represented by the exact locations and the corresponding uncertainties. Each node computes its belief on the location, which is a normalized estimate of the posterior likelihood of the location. The node communicates with neighbors on each other's belief and updates its location and the associated belief based on the information from neighbors. The process iterates until certain convergence criteria can be met. The fully distributed algorithm relies on local information and message exchanges, which invokes less communication and computation cost as compared to centralized algorithms.

Model based localization can be viewed as alternative to the map-assisted localization. Instead of deterministic relationships between range measurements and location estimates, model based localizations employ probabilistic models for range measurements and location estimates. For instance, a method proposed in [42] is based on the probabilistic model of RSS that is obtained in the calibration phase using experimental data from an outdoor environment without obstructions. In the subsequent localization phase, anchor nodes and non-anchor nodes with updated estimations on their locations send out beacons to the neighbors. Upon receiving the beacon packets, the probability density functions of the non-anchor nodes are updated accordingly. Finally, the location of a non-anchor node is given by the estimated coordinates with the highest probability.

There is also a reference to the use of Bayesian models for the noisy distance measurements [43]. Before being applied in the localization process, the models are trained with RSS measurements that are collected in an office building. An observation on the training procedure is that the locations of the training data does not affect the localization performance given the same sample size of training data. This observation indicates a promising feature of using hierarchical Bayesian graphical model. When gathering RSS data for training the models, it is not necessary to collect the location information of the RSS data.

4 Performance comparison

This section focuses on the evaluation of localization schemes. We compare a group of typical solutions that reveal the tradeoffs among different evaluation metrics.

4.1 Evaluation metrics

The three basic evaluation metrics consist of computation and communication costs, localization accuracy, and network density.

Localization accuracy

Localization accuracy relies largely on the physical sources of localization errors. The physical sources are represented by a wide range of noises and quantization losses of range measurements. A summary on the range accuracy of various ranging techniques was presented in [44]. Among these techniques, the most attractive ones are those with low cost and ready-to-use features like TOA or RSSI. The only concern about these techniques is that they produce highly noisy measurements and are over sensitive to environmental effects.

Since range errors are inherent to WSNs employing simple and low-cost ranging hardware, it is important to determine the impact of range error on the performance of localization algorithms. According to empirical studies [45], high node density and Gaussian noises are the two prerequisites for the use of the noisy disk model, which introduces noise component in the popular Unit Disk range model. It also suggests probabilistic approaches in reducing the impact of range errors.

The Cramer-Rao lower bound (CRLB) is commonly adopted in the error analysis of the localization schemes. It is a lower bound on the variance of the estimator for locations. Given the knowledge of the range distribution, the bound on the localization error can be derived accordingly [46]. Therefore, localization schemes are able to evaluate their performances by comparing the localization accuracy with the corresponding CRLB.

Computation and communication costs

As energy efficiency is critical to WSNs, it is necessary to minimize both computation and communication costs in any operation involving WSNs. Centralized localization algorithms like the SDP or MDS-MAP demand range measurements from all the nodes. This is expensive in terms of forwarding the measurements to the processing node and solving the high dimension matrix. Distributed algorithms, on the other hand, require collaborations among neighboring nodes. In particular, the multihop localization faces the tradeoff between the communication cost on propagating the anchor locations and the degree of accuracy. The number of iterations in a localization process is apparently in the center of the tradeoff between the energy consumption for refinement of localization results and the degree of accuracy achievable through refining.

Network and anchors density

The discussions on the localization algorithms suggest that dense networks lead to better localization performance. The anchor-based localization schemes require a high density of anchors that is essential to ensure low level of localization error. However, a dense network does not necessarily guarantee high accuracy in location estimations.

4.2 Summary of localization performances

As already discussed, existing localization solutions were generally proposed to cater to the requirements of different application scenarios. The difficulty of comparing their results is exacerbated by the fact that different test-beds were built for the purpose of evaluations, at times restricted to applications at hand. Still, we can summarize the performance of solutions with respect to accuracy, communication/computation costs and node density.

Table 1 shows that the localization accuracy was examined on the basis of tradeoffs between accuracy, computational complexity, communication cost, deployment of anchors, density of non-anchors, etc. Apart from randomly generated networks, a typical deployment of nodes is a grid of non-anchor nodes within a particular area. The localization accuracy is usually quantified using the average Euclidean distance between the estimated locations and the actual locations normalized to the radio range or other system parameters. For mobility-assisted localizations, the impact of node density is not as important as for localization of static nodes. In addition, communication/computation costs may not be of the same importance to off-line simulations as to real implementations.

Table 1 Performance summary of localization schemes.

Methods	Accuracy	Computation/Communication costs	Node density
APIT [24]	$40\%R$	10% message overhead of DV-hop	16 one-hop anchors
DV-hop [27]	$30\%R$ for isotropic topology $90\%R$ for anisotropic topology	Number of messages exchanged: 7000	$Nd=7.6$ with 30% to be anchors
DV-distance [27]	$15\%R$ for isotropic topology $80\%R$ for anisotropic topology	Number of messages exchanged: 7200	$Nd=7.6$ with 30% to be anchors
Euclidean [27]	$10\%R$ for isotropic topology $15\%R$ for anisotropic topology	Number of messages exchanged: 8000	$Nd=7.6$ with 30% to be anchors
MDS-MAP [28]	$50\%R$	Computational complexity: $O(n^3)$	$Nd \geqslant 12.2$ 3 anchors at random positions
Kernel-based learning [40]	$35.3\%D$	Worst case Computational complexity: $O(n^3)$	25 anchors covering 40 inches $\times$ 40 inches area
MCL [35]	$20\%R$	50 samples from the full distribution	10 nodes in one radio range 4 anchor nodes in one radio range
RSS Model [13]	$5\%R$	$O(n^2 \log_2 n)$	0.5 nodes/m^2

The table only shows typical values of the metrics, though a series of metric values were reported in literature. For the sake of conciseness, radio range and average node degree is denoted by R and Nd, respectively, while D represents the average inter-distance of anchors.

5 Open issues

Although there has been extensive research on sensor localization, some issues still remain unresolved or unexplored as discussed below.

Energy consumption

Although energy consumption has been addressed in localization of WSNs, designing energy efficient localization schemes is quite challenging. Incorporating energy efficient design at the communication layers and all aspects of a localization algorithm for a WSN requires evolution of an appropriate model for quantifying energy consumption. Obviously, this is a non-trivial task as it covers many unrelated tasks such as localization related measurements, communication among neighbors and estimating locations, among others.

3-Dimensional WSNs

The typical scenario for localization in WSNs is to determine the locations of the nodes in a 2-D plane. However, many deployments are in a 3-D space. Therefore, it leads to differences on both ranging results and localization algorithms. Analysis on localization schemes focusing on the 3-D space is of particular interest to real applications of WSNs, especially when the difference between localizations in 2-D place and 3-D space is significant. For instance, irregularity of the radio transmission has been investigated in 2-D space [47], while its counterpart in 3-D space remains unexplored.

Security and privacy

Security and privacy have always been major issues in wide deployment of WSNs. On the one hand, knowing locations of nodes with good accuracy could be important to some applications. On the other hand, revealing locations to the applications that do not need them, may leave the WSNs open to security and privacy attacks. For example, security of WSNs could be very critical to operations of smart environments. Although some research on security of localization schemes has been recently reported [48, 49], the types of attacks and the related countermeasures are restricted to a few typical cases. Similarly, privacy of node locations is not protected in most localization processes.

6 Conclusions

This paper dealt with the localization problems in WSNs. In the literature, localization methods are normally referred to either as range-based or range-free. However, such a broad classification is grossly inadequate, because it restricts classification to hardware requirements of the localization schemes. As discussed in this paper, we believe a more elaborate taxonomy that also deals with the solution characteristics and application requirements would be more appropriate. To justify the proposed line of investigation, we reviewed existing solutions, discussed the complexities of using proximity information, range measurements or both. In addition, mobility-assisted localization, localization of mobile nodes and probabilistic approaches are also reviewed in detail. Subsequently, a summary of qualitative evaluation of important localization schemes is presented on the basis of accuracy, computation/communication costs and node density. Some open issues for further research have been included.

References

[1] H. M. Ammari, S. K. Das. Integrated coverage and connectivity in wireless sensor networks: A two-dimensional percolation problem[J]. *IEEE Transactions on Computers*, 2008, 57(10): 1423 – 1434.

[2] F. Kuhn, R. Wattenhofer, A. Zollinger. Worst-case optimal and average-case efficient geometric ad-hoc routing[C]//*Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking & Computing*. New York: ACM, 2003: 267 – 278.

[3] H. Qu, S. B. Wicker. Co-designed anchor-free localization and location-based routing algorithm for rapidly-deployed wireless sensor networks[J]. *Information Fusion*, 2008, 9(3): 425 – 439.

[4] T. Gu, H. K. Pung, D. Zhang. A service-oriented middleware for building context-aware services[J]. *Journal of Network and Computer Applications*, 2005, 28(1): 1 – 18.

[5] A. Savvides, M. Srivastava, L. Girod, et al. Localization in sensor networks[M]//*Wireless Sensor Networks*. Massachusetts: Kluwer Academic Publishers, 2004: 327 – 349.

[6] J. Bachrach, C. Taylor. Localization in sensor networks[M]// *Handbook of Sensor Networks: Algorithms and Architectures*. Hoboken: John Wiley & Sons, 2005: 277 – 310.

[7] G. Mao, B. Fidan, B. D. Anderson. Wireless sensor network localization techniques[J]. *Computer Networks*, 2007, 51(10): 2529 – 2553.

[8] A. Nasipuri, K. Li. A directionality based location discovery scheme for wireless sensor networks[C]//*Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications*. New York: ACM, 2005: 105 – 111.

[9] D. Niculescu, B. Nath. DV based positioning in ad hoc networks[J]. *Telecommunication Systems*, 2003, 22(1/4): 267 – 280.

[10] M. L. Sichitiu, V.Ramadurai. Localization of wireless sensor networks with a mobile beacon[C]//*IEEE International Conference on Mobile Ad-hoc and Sensor Systems*. Piscataway: IEEE, 2004: 174 – 183.

[11] R. Huang, G. Zaruba. Incorporating data from multiple sensors for localizing nodes in mobile ad hoc networks[J]. *IEEE Transactions on Mobile Computing*, 2007, 6(9): 1090 – 1104.

[12] H. Lim, L.-C. Kung, J. C. Hou, et al. Zero-configuration, robust indoor localization: Theory and experimentation[C]//*Proceedings of the 25th IEEE International Conference on Computer Communications*. Piscataway: IEEE, 2006: 1 – 12.

[13] R. Peng, M. L. Sichitiu. Probabilistic localization for outdoor wireless sensor networks[J]. *SIGMOBILE Mobile Computing and Communications Review*, 2007, 11(1): 53 – 64.

[14] A. Savvides, C.-C. Han, M. B. Strivastava. Dynamic fine-grained localization in ad-hoc networks of sensors[C]//*Proceedings of the 7th Annual International Conference on Mobile Computing and Networking*. New York: ACM, 2001: 166 – 179.

[15] M. Youssef, A. Youssef, C. Rieger, et al. Pinpoint: An asynchronous determination time-based location determination system[C]// *Proceedings of the 4th International Conference on Mobile Systems, Applications and Services*. New York: ACM, 2006: 165 – 176.

[16] T. Eren, O. Goldenberg, W. Whiteley, et al. Rigidity, computation, and randomization in network localization[C]//*Proceedings of the Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2004: 2673 – 2684.

[17] J. Aspnes, D. Goldenberg, Y. R. Yang. On the computational complexity of sensor network localization[C]//*Proceedings of First International Workshop on Algorithmic Aspects of Wireless Sensor Networks*. Berlin: Springer-Verlag, 2004: 32 – 44.

[18] P. Stoica, K. Sharman. Maximum likelihood methods for direction-of-arrival estimation[J]. *IEEE Transactions on Acoustics, Speech and Signal Processing*, 1990, 38(7): 1132 – 1143.

[19] N. B. Priyantha, A. Chakraborty, H. Balakrishnan. The cricket location-support system[C]//*Proceedings of the 6th Annual International Conference on Mobile Computing and Networking*. New York: ACM, 2000: 32 – 43.

[20] D. Niculescu, B. Nath. Ad hoc positioning system (APS) using AOA[C]//*Proceedings of the Twenty-Second Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2003: 1734 – 1743.

[21] J. Bruck, J. Gao, A. A. Jiang. Localization and routing in sensor networks by local angle information[C]//*Proceedings of the 6th ACM International Symposium on Mobile Ad Hoc Networking and Computing*. New York: ACM, 2005: 181 – 192.

[22] N. Bulusu, J. Heidemann, D. Estrin. GPS-less low-cost outdoor localization for very small devices[J]. *IEEE Personal Communications*, 2000, 7(5): 28 – 34.

[23] P. Agrawal, R. K. Ghosh, S. K. Das. Localization of wireless sensor nodes using proximity information[C]//*Proceedings of the 16th International Conference on Computer Communications and Networks*. Piscataway: IEEE, 2007: 485 – 490.

[24] T. He, C. Huang, B. M. Blum, et al. Range-free localization and its impact on large scale sensor networks[J]. *ACM Transactions on Embedded Computing System*. 2005, 4(4): 877 – 906.

[25] H.-C. Chu, R.-H. Jan. A GPS-less, outdoor, self-positioning method for wireless sensor networks[J]. *Ad Hoc Networks*, 2007, 5(5): 547 – 557.

[26] R. Nagpal, H. Shrobe, J. Bachrach. Organizing a global coordinate system from local information on an ad hoc sensor network[C]// *Proceedings of the 3rd International Symposium on Information Processing in Sensor Networks*. New York: ACM, 2003: 21 – 32.

[27] D. Niculescu, B. Nath. Ad hoc positioning system (APS)[C]// *Proceedings of the IEEE Global Telecommunications Conference*. New York: IEEE, 2001: 2926 – 2931.

[28] Y. Shang, W. Ruml, Y. Zhang, et al. Localization from mere connectivity[C]//*Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking & Computing*. New York: ACM, 2003: 201 – 212.

[29] K. Chintalapudi, A. Dhariwal, R. Govindan, et al. Ad-hoc localization using ranging and sectoring[C]//*Proceedings of the Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2004: 2662 – 2672.

[30] L. Doherty, K. Pister, L. E. Ghaoui. Convex position estimation in wireless sensor networks[C]//*Proceedings of the Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2001: 1655 – 1663.

[31] P. Biswas, T.-C. Lian, T.-C. Wang, et al. Semidefinite programming based algorithms for sensor network localization[J]. *ACM Transactions on Sensor Networks*, 2006, 2(2): 188 – 220.

[32] X. Ji, H. Zha. Sensor positioning in wireless ad-hoc sensor networks using multidimensional scaling[C]// *Proceedings of the Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2004: 2652 – 2661.

[33] D. Moore, J. Leonard, D. Rus, et al. Robust distributed network localization with noisy range measurements[C]//*Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems*. New York: ACM, 2004: 50 – 61.

[34] S. Capkun, M. Hamdi, J.-P. Hubaux. GPS-free positioning in mobile ad-hoc networks[C]//*Proceedings of the 34th Annual Hawaii International Conference on System Sciences*. Los Alamitos: IEEE Computer Society, 2001.

[35] L. Hu, D. Evans. Localization for mobile sensor networks[C]// *Proceedings of the 10th Annual International Conference on Mobile Computing and Networking*. New York: ACM, 2004: 45 – 57.

[36] C. Taylor, A. Rahimi, J. Bachrach, et al. Simultaneous localization, calibration, and tracking in an ad hoc sensor network[C]//*Proceedings of the 5th International Conference on Information Processing in Sensor Networks*. New York: ACM, 2006: 27 – 33.

[37] K. Sreenath, F. L. Lewis, D. O. Popa. Simultaneous adaptive localization of a wireless sensor network[J]. *SIGMOBILE Mobile Computing and Communications Review*, 2007, 11(2): 14 – 28.

[38] P. Dang, P. Ballal, F. L. Lewis, et al. Real time relative and absolute dynamic localization of air-ground wireless sensor networks[J]. *Journal of Intelligent and Robotic Systems*, 2008, 51(2): 235 – 257.

[39] P. Bahl, V. N. Padmanabhan. RADAR: An in-building RF-based user location and tracking system[C]// *Proceedings of the Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2000: 775 – 784.

[40] X. Nguyen, M. I. Jordan, B. Sinopoli. A kernel-based learning approach to ad hoc sensor network localization[J]. *ACM Transactions on Senor Networks*, 2005, 1(1): 134 – 152.

[41] E. T. Ihler, J. W. Fisher, O. L. Moses, et al. Nonparametric belief propagation for self-localization of sensor networks[J]. *IEEE Journal on Selected Areas in Communications*, 2005, 23(4): 809 – 819.

[42] R. Peng, M. L. Sichitiu. Probabilistic localization for outdoor wireless sensor networks[J]. *SIGMOBILE Mobile Computing and Communications Review*, 2007, 11(1): 53 – 64.

[43] D. Madigan, E. Einahrawy, R. P. Martin, et al. Bayesian indoor positioning systems[C]//*Proceedings of the 24th Annual Joint Conference of the IEEE Computer and Communications Societies*. Piscataway: IEEE, 2005: 1217 – 1227.

[44] A. Savvides, W. Garber, R. Moses, et al. An analysis of error inducing parameters in multihop sensor node localization[J]. *IEEE Transactions on Mobile Computing*, 2005, 4(6): 567 – 577.

[45] K. Whitehouse, C. Karlof, A. Woo, et al. The effects of ranging noise on multihop localization: an empirical study[C]//*Proceedings of the Fourth International Symposium on Information Processing in Sensor Networks*. New York: ACM, 2005: 73 – 80.

[46] S. Venkatesh, R. M. Buehrer. Multiple-access insights from bounds on sensor localization[J]. *Pervasive and Mobile Computing*, 2008, 4(1): 33 – 61.

[47] G. Zhou, T. He, S. Krishnamurthy, et al. Models and solutions for radio irregularity in wireless sensor networks[J]. *ACM Transactions on Sensor Networks*, 2006, 2(2): 221 – 262.

[48] Z. Li, W. Trappe, Y. Zhang, et al. Robust statistical methods for securing wireless localization in sensor networks[C]//*Proceedings of the Fourth International Symposium on Information Processing in Sensor Networks*. New York: ACM, 2005: 91 – 98.

[49] L. Lazos, R. Poovendran. SeRLoc: Robust localization for wireless sensor networks[J]. *ACM Transactions on Sensor Networks*, 2005, 1(1): 73 – 100.

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