Sensor Localization under Limited Measurement Capabilities

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Abstract

In this article we survey the latest progress on sensor localization, focusing on distance measurement techniques and localization algorithms for a sensor to determine its own location. We illustrate why inaccurate distance measurements, arising from tight hardware design constraints, raise challenges in sensor localization and how proposed approaches strive to overcome these challenges. We conclude that sensor localization algorithms must be designed to accommodate different application requirements in terms of costs, energy consumption, and localization accuracy.

Determining the locations of sensors is a critical task in sensor network research because it provides the fundamental support for many protocols and applications. For example, some routing protocols in wireless networks use sensor location to assist in routing [1, 2]. Also, applications such as battlefield surveillance, habitat monitoring, and disaster mitigation require sensed data to be labeled with location information, so each sensor must be aware of its own position. The positions of sensors, however, cannot always be manually measured or simply acquired by Global Positioning System (GPS) receivers because both are costly when applied to numerous disposable sensors, and manual measurement is impractical when sensors are deployed in inaccessible areas such as volcanoes. Sensors may also be deployed in indoor environments, wild habitats with heavy vegetation, or urban areas surrounded by skyscrapers, where GPS receivers may inaccurately locate sensors, or it may be impossible, due to poor signal reception. Considering cost, accuracy, and accessibility, it is necessary to seek a low-cost solution to accurately locate sensors even in extremely harsh environments.

If we abstract a sensor network as a network graph consisting of vertices and edges, where vertices represent sensor nodes and edges represent distance measurements between neighboring sensors, the sensor localization problem can be generalized as inferring coordinates of vertices from lengths of edges. In most sensor networks, a small number of sensors will have known locations; they are called *beacons*. In practice, sensor localization usually involves two basic steps:

- Measuring distances between pairs of sensors
- Inferring sensor coordinates from the measured distances through geometric computation

For example, by measuring distances from a sensor to three beacons, the sensor's position can be determined through a simple triangulation algorithm.

In spite of its simple mathematical description, sensor localization is a difficult problem in engineering. Due to the tight design constraints of low cost and small size, sensors often lack sufficient hardware resources to achieve accurate and long-range distance measurements. To compensate, numerous sensor localization algorithms have been proposed (some are briefly summarized in [3]). In this article we focus on the challenges raised by inaccurate and short-range distance measurements in sensor localization and how proposed approaches aim to overcome these challenges.

The article is organized as follows. We introduce the current distance measurement techniques in sensor networks; we discuss why inaccurate and short-range distance measurements raise challenges to sensor localization; and we discuss area-based, distance-based, sophisticated radio-model-based, and mobile-sensor-based approaches for addressing these challenges. Last, we identify potential research directions and provide a conclusion.

Distance Measurement Methods

Radio and ultrasound signals are widely used to measure distances in sensor networks where cost and dimensions are concerns.

Radio-Based Distance Measurements

Radio signals are related to distances in that their signal strength attenuates during propagation. The transmission distance between a pair of sensors can be inferred from the received signal strength (RSS) by the ideal radio propagation model RSS $\propto 1/d^n$, where d is the distance between the transceivers and n is the path loss exponent (an environment-dependent constant). Distances estimated from RSS, however, may have large errors because radio signals are susceptible to environmental interference. Radio signals can be reflected, diffracted, and scattered by obstacles, which creates a *multipath* effect in which radio signals are propagated along multiple transmission paths from a sender to a receiver. The signal strength may be weakened when the waves of multipath signals are out of phase, or reinforced when the waves of multipath signals have the same phase. The actual received signals are the vector sum of all the radio signals received along the different paths [4]. Last, obstructions can weaken radio signals during their transmission. This is called *shadowing* and results in measurement errors in the RSS approach.

While errors incurred by shadowing are random and difficult to eliminate, the errors incurred by multipath effect,

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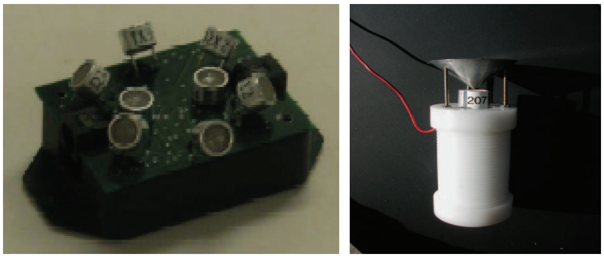


(a) (b)

■ Figure 1. *Solutions to unidirectional transmission of ultrasound: a) multiple microphones installed in a sensor to achieve omnidirectional ultrasound signal transmission; b) a cone reflector helps a sensor reflect ultrasound signals in multiple directions.*

which is a function of the radio frequency, can be diminished using spread-spectrum methods [5]. In order to reduce the random errors incurred by the multipath effect of a single radio frequency, the spread-spectrum method averages the RSS over a wide range of radio frequencies. The statistical properties of the radio-based RSS approach were discussed in [6], which concluded that the measurement error of the RSS approach is proportional to its measured distance. This happens because weak radio signals attenuated by long-distance transmission can easily be interfered with by background noise.

We can also obtain the distance between a pair of sensors by measuring the time of flight (TOF) of radio signals from a sender to a receiver. Since the flight speed of radio signals is constant, the distance between a pair of sensors can be computed by multiplying the TOF by the signal speed. Because radio signals propagate at extremely high speeds, meaningful one-way measurements can only be achieved with highly precise clocks that are synchronized between the sender and receiver. Clock synchronization can be avoided by measuring round-trip TOF at the sender, but the signal process delay incurred by the receiver circuit needs to be filtered. Clock synchronization can also be avoided by measuring the differences of TOF from a transceiver to multiple beacons with synchronized and precise clocks. For example, sensors with GPS receivers can estimate their own positions by referring to satellite beacons. Here, only the satellite beacons need to be equipped with synchronized and precise atomic clocks.

The major sources of measurement errors in the TOF approach are the multipath effect, clock drift, and clock resolution. In order to achieve accurate measurement, the TOF approach must precisely identify the first arrival of radio signals along the line-of-sight path between a pair of sensors. However, radio signals of the line-of-sight path may be interfered with by other radio signals transmitted along reflected paths. As discussed before, this multipath effect is frequency-selective. If ultra-wideband (UWB) radios with a wide range of frequencies are applied to the TOF approach, the probability of identifying the first arrival of the radio signals transmitted along the line-of-sight path can be increased [7]. Here, the UWB approach improves the measurement accuracy at the cost of using more bandwidth resources.

Ultrasound-Based Distance Measurements

Ultrasound signals are suitable for sensor networks because accurate distance measurement can be achieved at relatively low cost. Since the speed of ultrasound signals is relatively slow (approximately 331.4 m/s), their transmission delay is measurable by inexpensive clocks. Thus, the ultrasound-based TOF approach is feasible with low-cost sensors.

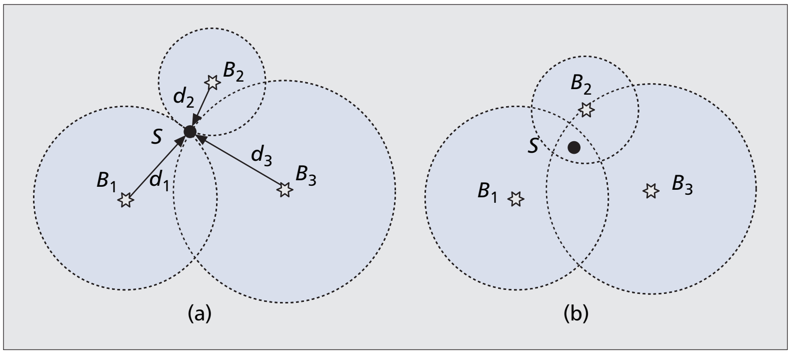
The ultrasound-based TOF approach, however, has three limitations in its distance measurement. First, the approach can achieve accurate distance measurement only when a line-of-sight path exists between pairs of sensors. Similar to radio signals, ultrasound signals also experience the multipath effect during their transmission. Since ultrasound signals spend more transmission time along the reflected paths than the line-of-sight path, the multipath effect can be filtered out by reading the earliest arriving signals. However, if the line-of-sight path is blocked, the measured distance may have large errors. Second, ultrasound signals are unidirectional, so for all receivers around a transmitter to receive a signal, either multiple microphones can be installed or a cone reflector can be used (Fig. 1). Third, because ultrasound signals attenuate fast and cannot propagate long distances, the ultrasound TOF approach has a short measurable range.

Distance Measurement Comparison

Table 1 summarizes the comparison of the three distance measurement approaches discussed above. The data is based on current implementation of MICA2 sensors [8]. The comparison illustrates that distance measurements in sensor networks either have low accuracy (radio-based) or short measurement ranges (ultrasound-based), making sensor localization a difficult problem. It is worth noting that ultrasound-based TOF is generally used in indoor environments because of the short ranges involved, and radio-based RSS is generally used outdoors where covered ranges are much larger.

	Radio-based RSS	Radio-based TOF (GPS)	Ultrasound-based TOF
Accuracy in good conditions	2 ~ 4 m	5 ~ 10 m	2 cm
Maximum range	100 m	Unlimited	10 m
Dimension	0	Matchbox size	43 mm × 20 mm × 17 mm
Power	75 mW	175 mW	75 mW
Environmental interference	Shadowing effects lead to unpredictable results	Affected by heavy trees and buildings, almost useless in indoor environments	Accurate in line-of-sight path, affected when line-of-sight path is blocked by obstructions
Cost	0	≤ $100	≤ $60

■ Table 1. *Comparison chart of distance measurement.*



■ Figure 2. *Impact of measurement errors on a triangulation algorithm.*

Challenges of Sensor Localization

A practical localization algorithm should tolerate distance measurement errors, deal with short-range measurements, and incur low communication and computation cost.

Measurement Errors

The triangulation algorithm is a basic method used to recover sensor position from the constraints of distance measurements. It operates as follows. When the measured distance d_i between sensor S and beacon B_i (i = 1, 2, 3) is available, the position of S is determined as the intersection point of the three circles with radius d_i (Fig. 2a). But when the distance measurements have errors, the three circles will not intersect at one point, meaning the position of S cannot be uniquely determined (Fig. 2b). Since distance measurement errors are inevitable in practice, sensor localization algorithms must approximate the location of S in a way that minimizes the positioning error.

When sensors are deployed in a complex area abundant with obstructions, line-of-sight paths may be blocked between pairs of sensors. As a result, distance measurements may deviate significantly from their true values. Large errors are regarded as *outliers* that could severely corrupt the final localization results. How to identify and exclude outliers is a challenging task because sensors usually have no visualization capability to detect obstructions.

Distance Measurement Range Limitations

Because distance measurements in sensor networks are short-range (due to design constraints on energy consumption and size), there may be insufficient measurements to uniquely determine sensor positions. A simple example is given in Fig. 3, which shows that the relative structure of the network cannot be known without sufficient distance measurements. In Fig. 3a only four measurements are known, so the network structure could be any of an infinite set of non-equivalent quadrangles (two are shown). In Fig. 3b all distance measurements between pairs of sensors are known, so the relative structure can be uniquely determined. But note that at least one of the added cross-measurements will necessarily be larger than the side measurements, so it may not be available given sensor distance measurement limitations.

Communication and Computation Cost

Sensors need to be low-cost so that they can be deployed in large numbers. As a result, hardware resources for computation and communication are limited. For example, current MICA2 sensors use Atmega128 8-bit microcontrollers that have maximum 16 MIPS throughput at 16 MHz. Furthermore, the programmable flash memory of MICA2 sensors is only 128 kbytes. Thus, any localization algorithm using this equipment must avoid intensive computation. In addition, because sensors with low-power radio transmitters can only communicate with nearby neighbors, multihop forwarding is widely used for message transmission, which is the primary source of energy consumption for a sensor network. In order to save energy and extend the lifetime of a sensor network, a good localization algorithm should minimize the number of messages it sends.

In the following sections we detail how current sensor localization algorithms provide solutions to the challenges outlined above.

Area-Based Algorithms

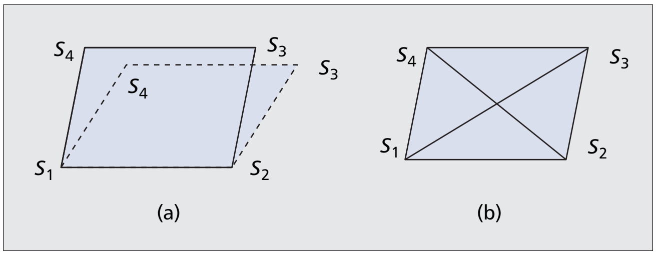
Radio connectivity is widely used to roughly estimate if two sensors are within the maximum radio signal transmission range. Based on the radio connectivity between pairs of sensors, area-based algorithms have been proposed to estimate a sensor's position from the polygon formed by surrounding beacons.

The idea of the **centroid** approach [9] is to estimate sensor location as the center of this polygon (Fig. 4a). The centroid approach assumes that beacons are densely and uniformly distributed such that each sensor can be surrounded by multiple beacons. The accuracy of this approach depends on the size of polygons formed by beacons. Higher accuracy can be obtained when a sensor is constrained in a smaller polygon, which can be achieved by reducing the radio transmission range of beacons such that a polygon is formed only by beacons within a shorter distance to the sensor. However, some sensors may lose radio connectivity to beacons with reduced radio transmission range, and therefore fail to locate themselves.

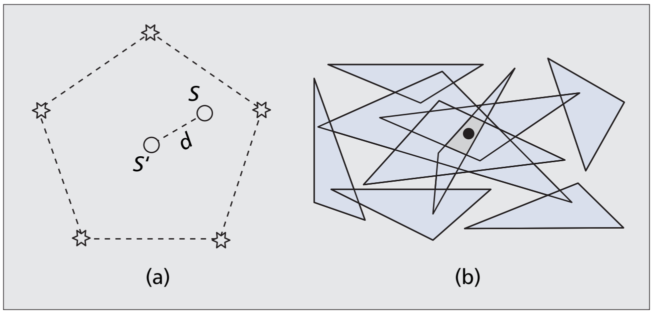
In order to increase localization accuracy, the **APIT** approach [10] has been proposed to exploit beacon redundancy. As illustrated in Fig. 4b, APIT selects groups of three beacons from the set of beacons that have radio connectivity to the sensor and forms a triangle for each group. For each triangle, the sensor decides if it is within the triangle based on signal strength (see [10] for details). Multiple triangles are formed from different combinations of available beacons. The location of the sensor can be pinpointed to the intersection area of all the triangles that contain the sensor. Since a smaller intersection area can be obtained from multiple overlapping triangles, the APIT approach can achieve higher localization accuracy than the basic centroid approach.

Distance-Based Algorithms

Unlike area-based algorithms that estimate positions of sensors from radio connectivity, distance-based algorithms use distance knowledge between pairs of sensors. Distance-based algorithms can be further divided into three categories: multilateration approaches, recursive approaches, and global optimization approaches.



■ Figure 3. *Network rigidity in sensor localization: a) network structure can be deformed; b) network structure can be determined.*



■ Figure 4. *Area-based algorithms: a) in the centroid approach the estimated position S′ of sensor S is calculated as the center of a polygon formed by beacons; b) in the APIT approach the position of a sensor is determined by the intersection area of multiple triangles.*

Multilateration Approaches

As discussed before, when distance measurements between a sensor and beacons have errors, the triangulation algorithm will fail to find a feasible position that can simultaneously satisfy all the distance measurements. An alternative solution called multilateration [11] has been proposed that computes an approximated location for the sensor by minimizing the error between the measured and approximated locations. Multilateration is illustrated in Fig. 5, where sensor P_0 has beacons P_i $(1 \le i \le n)$ as its immediate neighbors, and d_i is the measured distance between P_0 and P_i. The approximated position $\hat{P}_0$ of P_0 is determined by minimizing the differences between the estimated distance $|P_0P_i|$ and the measured distances d_i $(1 \le i \le n)$:

$$\hat{P}_0 = \arg\min_{P_0} \sum_{i=1}^{n} \left(|P_0 P_i| - d_i \right)^2 .$$

Unlike the triangulation algorithm, which tries to find a sensor's position whose distances to beacons are exactly equal to the corresponding measured distances, the multilateration approach aims to find a sensor's position that minimizes the differences between estimated distances and measured distances. This distance fitting approach is based on the belief that all measured distances have the same error distributions and should be fitted equally. By fitting each measured distance as close as possible, the multilateration approach finds out the optimal position that is close to the true position with a high probability. It is notable that the multilateration approach cannot tolerate large distance measurement errors.

For a sensor to be successfully located by multilateration, at least three beacons must be within the distance measurement range. However, a sensor network usually has short-range distance measurement, and when beacons are sparsely distributed it is unlikely for all sensors to have three beacons or more as their immediate neighbors. In order to obtain distances between a sensor and beacons that are several hops away, the **multihop** approach [12] has been proposed to approximate the distance between a pair of sensors as the length of the shortest path connecting them. The approach infers distances from each sensor to all beacons as the lengths of the shortest paths between them using the same algorithm as in distance vector routing.

The multihop approach achieves the capability of long-range distance measurement by sacrificing measurement accuracy in that the length of the shortest path is often greater than the Euclidean distance between a pair of sensors. In order to combine the advantages of the long-range measurement of the multihop approach and the measurement accuracy of *one-hop* approaches, the **two-phase** localization algorithm [13] has been proposed to locate sensors in two steps. In the startup step the multihop approach is used to roughly estimate each sensor's initial position based on its distances to beacons that may be several hops away. In the refinement step each sensor can further improve the positioning accuracy by exchanging its initial position with its neighbors that are one hop away. The refinement process can be iteratively applied as long as a sensor receives position updates from its neighbors.

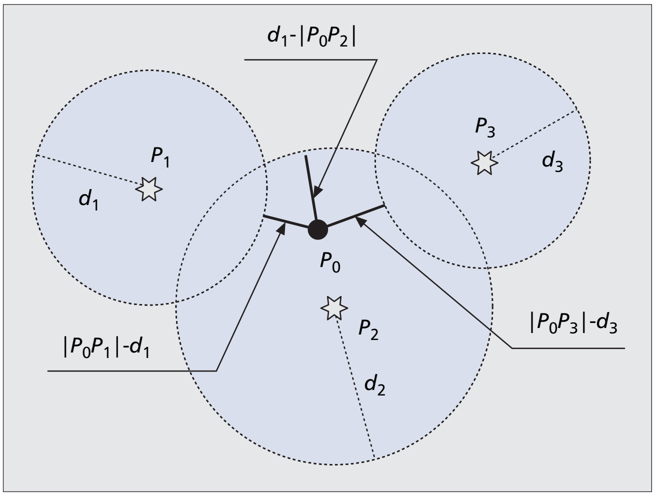
The multihop approach may have large distance measurement errors when the intermediate nodes of the shortest path are not aligned in a straight line, which often happens in a sensor network with a nonuniform node distribution. To solve this problem, the proximity-distance map (PDM) [14] has been proposed to accurately infer distances from lengths of the shortest paths between pairs of sensors. In PDM each sensor is assigned an M-dimensional coordinate defined by the number of hops of the shortest paths from the sensor to all M beacons:

$$\vec{p}_i = [p_{i1}, \ldots p_{iM}]^T.$$

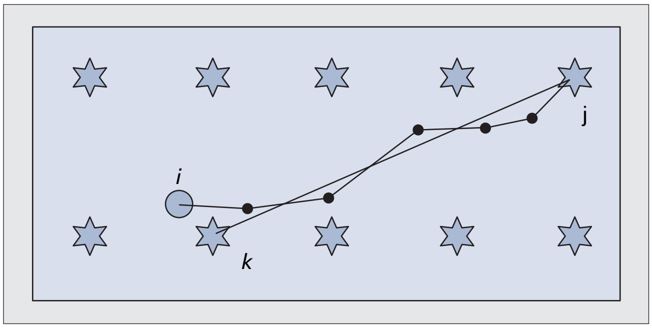
Here, p_{ij} is the number of hops of the shortest path from sensor i to beacon j. The objective of PDM is to find the M-dimensional coordinate of sensor defined by the distances from the sensor to all M beacons:

$$\vec{l}_i = [l_{i1}, \ldots l_{iM}]^T.$$

Here, l_{ij} is the distance from sensor i to beacon j. Based on the distances l_{ij} to multiple beacons, the position of sensor i can be determined by the multilateration approach. PDM assumes a linear transformation between the coordinates $\vec{p}_i$ and $\vec{l}_i$ such that $\vec{l}_i = T\vec{p}_i$, where T is the transformation matrix and can be learned from beacons. The PDM algorithm is intuitively explained in Fig. 6, where sensor i is several hops away from beacon j. If we use the multihop approach, the distance between sensor i and beacon j can be calculated as $l_{ij} = t\,p_{ij}$, where t is the average length of one hop. The distance estimated by the multihop approach has large error because the shortest path cannot be aligned in a straight line in a sensor network with nonuniform node distribution. Instead of directly inferring the distance l_{ij} by multiplying p_{ij} with the single coefficient t, the PDM algorithm uses matrix T comprising a group of weighted coefficients to obtain the distance. In Fig. 6 sensor i has almost the same distance to beacon j as to beacon k because sensor i and beacon k are close to each other. As a result, distance l_{ij} can be approximated by distance l_{jk}. Here, l_{jk} can be accurately determined by the prior position



■ Figure 5. *The multilateration approach.*



■ Figure 6. *An example of the PDM algorithm.*

knowledge of beacons k and j. This approximation is realized by the PDM algorithm by assigning beacon k a large weight such that distance l_{ij} is primarily determined by distance l_{jk}.

The multihop approach may incorrectly estimate distances between pairs of sensors when they are deployed in a concave area (a region in which the shortest distance between some pair of sensors lies outside the region). In such a region the length of the shortest path may deviate far away from the true distance. The incorrect distance measurements are regarded as outliers that could severely corrupt the final localization result. An example is shown in Fig. 7a, in which the length of the shortest path between P_3 and P_4 is much longer than their Euclidean distance. In such a case, if we use the basic multilateration approach, the estimated position of sensor P will be pushed far away from its true position by the outlier. To exclude such outliers, the **upper bound approach** [15] has been proposed to enforce upper bound constraints on distance measurements in multilateration:

$$\hat{P}_0 = \arg\min_{P_0} \sum_{i=1}^{n} \left(|P_0P_i| - d_i\right)^2 \text{ subject to } |P_0P_i| \le d_i.$$

The upper bound approach is based on the observation that the distance measurements in a concave network are upper bounds on their true values. By imposing this constraint, the sensor's estimated position will lie in the intersection area that contains the true position of sensor P as shown in Fig. 7b.

Recursive Approaches

Recursive approaches [11, 16] are alternative solutions for overcoming the limit of short-range distance measurements. In recursive approaches, a sensor will announce itself as a "new" beacon after its position is accurately determined. The newly joined beacons can be utilized by nearby sensors which could not locate themselves before due to insufficient beacons. By applying the whole process iteratively, "converted" beacons are propagated from the area that is closer to the startup beacons to the area where the startup beacons are inaccessible. An example is shown in Fig. 8, where node P5 (which cannot see P1) can be located after P4 is converted to a beacon.

The potential problem of recursive approaches is that the positioning error may accumulate along the iterative process and the final localization result can be severely corrupted. Thus distance measurements should be as accurate as possible. However, even if distances are accurately measured, the localization results may have large errors when beacons are placed in close to a straight line (Fig. 9a). Here a small error in distance measurement will cause the estimated position of sensor P0 to be flipped over to P0′.

The **robust quadrilaterals approach** [17] has been proposed to reduce the positioning ambiguity. The basic unit of the approach is the *robust quad*, which consists of four nodes fully connected by measurement distances as shown in Fig. 9b. Here, P1, P2, and P3 are beacons, and P0 is the node with unknown position. If P1, P2, and P3 are aligned in a straight line, the angle $\angle P1P2P3$ will have a small value. Consequently, the set of beacons aligned in a straight line can be identified and excluded based on the value of angle $\angle P1P2P3$.

Global Optimization Approaches

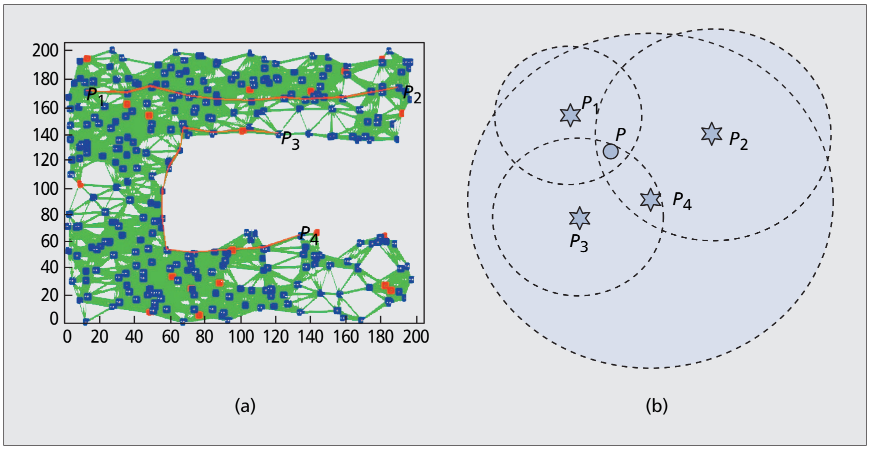
When beacons are sparsely distributed, it is possible that the recursive approach cannot be initiated because none of the sensors have sufficient beacons as their immediate neighbors. An example is shown in Fig. 10, where nodes S1 and S2 have unique positions but cannot be located by recursive approaches, because both of them only have two beacons within their measurement ranges.

The global optimization estimates sensor positions by solving the following objective function:

$$\min \sum_{(i,j)\in E} (e(i,j) - m(i,j))^2,$$

where $e(i,j)$ arethe estimated positions of sensor i and j, $m(i,j)$ is the measured distance between them, and E is the vertex set containing all sensors. The objective function estimates sensor position by fitting estimated distances to all measured distances.

Multidimensional Scaling (MDS) [18] has been suggested to solve the global objective function. Originating in psychometrics and psychophysics, MDS is a classic data analysis technique that visualizes the structure of distance-like data as a geometric picture. Aiming to solve a problem similar to sensor network localization, MDS was developed to find the space structure of vertices based on distance-like constraints between pairs of vertices. For example, given a map containing multiple cities with known coordinates, it is easy to compute the Euclidean distances between any pair of cities. However, the inverse problem cannot be solved as straightforwardly: given the knowledge of distances between pairs of



■ Figure 7. *Multihop approach in a concave area [15]: a) the multihop approach may have large distance estimation errors in a concave network; b) the estimated position is constrained to be in the area intersected by the upper bound constraints of distance measurements.*

cities, it is difficult to recover the coordinate of each city. The classic MDS technique was proposed to resolve the problem by solving the objective function above. However, the classical MDS requires distances between any pairs of nodes before it can successfully construct the coordinates of nodes. We can use the multihop based approach to obtain distances between any pairs of sensors, and apply the MDS algorithm to infer sensors' coordinates [19].

An improved MDS algorithm [20] has been proposed that can recover coordinates of sensors with partial distance measurements between pairs of sensors. By assigning zero weights to pairs of sensors between which distance measurements are not available, the improved MDS algorithm finds positions of sensors by fitting estimated distances to partially available measured distances.

MDS can calculate the relative coordinates of sensors without the presence of beacons. When a few beacons are known, the physical coordinates of the sensors can be recovered. This is realized through the operations of scaling, rotation, and reflection, which convert relative coordinates of beacons to their physical coordinates. The relative coordinates of sensors are then converted to physical coordinates.

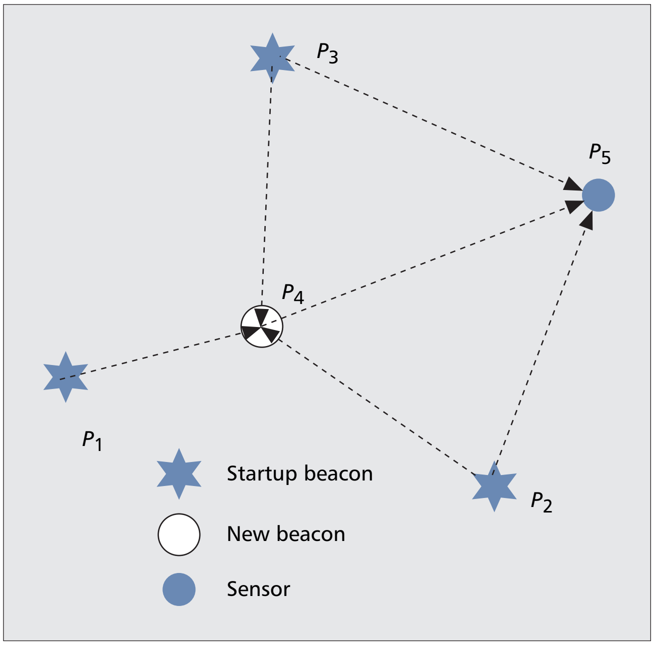
Compared to recursive approaches, the global optimization approach can locate sensors with fewer beacons. However, the MDS algorithm incurs intensive optimization computation that requires a powerful CPU and large memory, which cannot be realized in resource-constrained sensors. A possible solution is to realize the optimization computation within a base station.

Locating Sensors from Sophisticated Radio Transmission Models

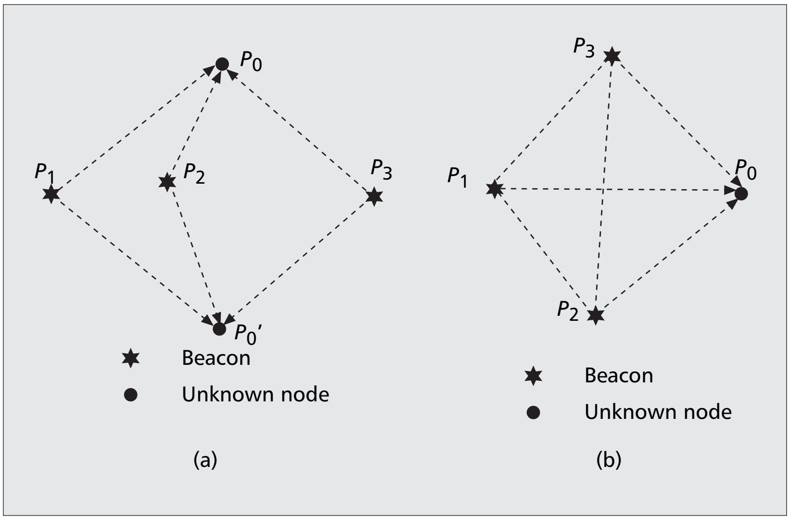
RSS-based distance measurement is inaccurate and can be unreliable because its ideal radio transmission model overlooks environmental interference. Instead of directly inferring distance from the simple radio distance model RSS $\propto 1/d^n$, more sophisticated radio transmission models have been proposed to accurately locate sensors by either canceling the environmental interference in distance measurement [21] or incorporating it into the localization algorithm [22].

In the Radio Interferometric Positioning System (RIPS) [21], two transmitters emit radio waves at slightly different frequencies to create radio interference. The relative phase offset of the interference signals measured at two receivers is the function of the distances between the four nodes. Because RIPS measures the relative difference of RSS between two receivers, the environmental interference that has the same impact on the two receivers can be canceled out in the distance estimation. It is reported in [21] that RIPS can measure distances up to the 160 m range with an average positioning error of 3 cm, which significantly improves the localization accuracy when compared with other radio based approaches.

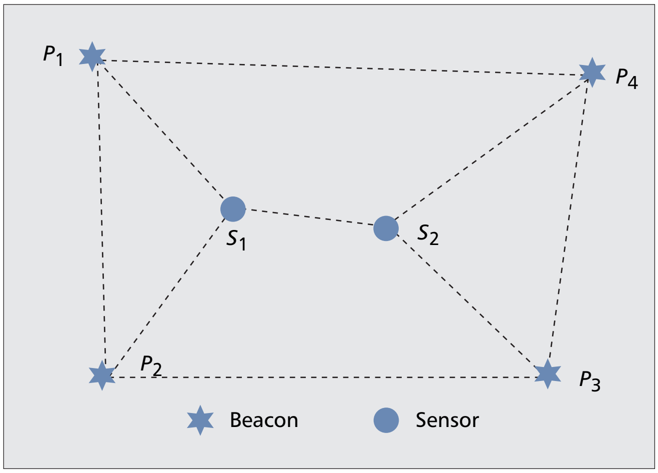
Similar to the indoor tracking systems [23], the **kernel-based learning** approach [22] tries to infer sensor location directly from the distribution pattern of radio signals instead of the distance knowledge between pairs of sensors. The learning-based approach models the sensor localization as a classification problem that decides if a sensor i is within a certain region C given the distribution pattern of radio signals measured by sensor i. The classification function is trained by the distribution pattern of radio signals measured by beacons.



■ Figure 8. *Recursive approach.*



■ Figure 9. *Ambiguity elimination in recursive approaches: a) Ambiguity in sensor localization; and b) robust quadrilaterals approach (adapted from [17]).*



■ Figure 10. *Global optimization approach.*

	APIT	Multihop	Robust quadrilaterals	MDS	Kernel-based learning
Distance measurements	Radio based connectivity model	Radio based connectivity model	Ultrasound based TOF	Radio based connectivity model	Radio Based RSS approach
Geometric algorithms	Extended Centroid algorithm	Least squares fitting	Least squares fitting	Multidimensional Scaling	Support vector machine
Number of beacons	Large	Small	Small	Zero or three	Large
Communication cost	Low, one hop beacon broadcast	High, broadcast beacon message to an entire network	Low, one hop beacon broadcast	High, broadcast message to an entire network	Low, one hop beacon broadcast
Computation cost	Low	Low	Low	High	High
Localization accuracy	≤ *R**	O(R)	O(cm)	O(R)	O(inch)
* R is the radio transmission range					

■ Table 2. *Comparison of localization algorithms.*

The learning-based approach is robust because the environmental interference on the distribution pattern of radio signals has been measured by beacons and incorporated in the classification function. In order to further improve the positioning accuracy, the kernel based learning approach divides the deployed area into multiple overlapped regions and pinpoints a sensor's position to a small intersection region. The kernel-based learning approach has been proved to be an effective algorithm when sensors are densely deployed [22].

Localization in a Mobile Sensor Network

In a mobile sensor network, any sensor can move. The localization algorithm needs to be more complex because it must track the changing sensor positions. Yet mobile beacons can present more opportunities for reference by sensors. Monte Carlo Localization (MCL) [24] utilizes this aspect in mobile sensor localization.

MCL divides time into discrete units and re-estimates positions of sensors in each time unit. MCL consists of two phases: prediction and filtering. In prediction, sensors predict their locations based on their prior location and their maximum speed v_{max}. (If l_{t-1} is the sensor location at time $t - 1$, the location at time t must be within a circle C centered at l_{t-1} with radius v_{max}.) The uncertainty of the result can be reduced by filtering. In the filtering phase each sensor observes nearby beacons and exchanges beacon information with its neighbors. If the maximum radio transmission range is r, the sensor knows that it is within distance r of any adjacent beacons. For any beacons that are not heard by the sensor but are heard by its neighbors, the sensor knows that the distances to those two-hop beacons are greater than r but less than $2r$. A sensor can thus learn that it is within the area S in which all points are within range r of the adjacent beacons and range $2r$ of the two-hop beacons. The final estimated position is the aggregated result of circle C in prediction phase and area S in the filtering phase, and expressed as a form of probability distribution.

Conclusion and Future Work

Due to the power, size, and cost constraints imposed on sensors, the distance measurements in sensor networks are often error-prone and short-range, making accurate sensor location a challenging task. Numerous localization algorithms have been proposed to compensate for the inaccurate distance measurements and recover sensor position as accurately as possible. Five representative algorithms are summarized in Table 2. A localization algorithm that can accurately locate sensors with low communication and computation cost has not been fully realized. Consequently, sensor localization is still an ongoing research area.

One challenge for further research is the implementation of accurate and long range distance measurement at low cost in sensor networks. If such implementation is prohibitive for each sensor, a hybrid solution can be adopted, in which a small set of powerful beacons provide accurate long-range distance measurements to the remaining sensors. Beacons that have mobile capabilities can roam in a network to make themselves easily accessible by sensors.

If the distance measurement is inevitably constrained by hardware, a robust localization algorithm needs to be developed that can tolerate individual measurement errors by exploiting the measurement redundancy of an entire network. Error-tolerant localization algorithms usually resort to optimization approaches, which minimize the differences between estimated distances and measured distances. Optimization algorithms, however, often demand intensive computations that are difficult to implement in resource-constrained sensors. As a result, additional work is needed on the implementation of efficient optimization algorithms in sensor nodes.

Sensor localization provides a basic service to sensor applications. The application makes the final decision on how accurate the localization algorithm should be and how much resources can be consumed. We should not expect a localization approach that provides universal positioning services to all applications. Instead, the localization approach should be application-oriented and designed according to the application requirements with appropriate trade-offs between accuracy and cost.

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