East West University

FALL -2017

Project Report

"Study on Range Free Localization in Wireless Sensor Network (WSN)"

Submitted by-

MD. Hasibul Islam Bhuiyan

ID: 2013-1-55-018

Md. Tanvir Ahmed Bhuiyan

ID: 2013-2-55-014

Atiar Rahhan Sunny

ID: 2013-2-55-009

Supervisor

Dr. Anup Kumar Paul

Assistant Professor

Department of Electronics and Communications Engineering

Declaration

I hereby declare that we have completed project on the topic entitled "**Study on Range Free Localization in Wireless Sensor Network (WSN)**" as well as prepared as research report to the department of Electronics and Communications Engineering, East West University in partial fulfillment of the requirement for the degree of B.Sc. in Electronics and Telecommunications Engineering, under the course "Research/Internship (ETE 498)". I further assert that this report in question is based on our original exertion having never been produced fully and/or partially anywhere for any requirement.

……………………..	……………………..	……………………..
MD.Hasibul Islam Bhuiyan	MD.Tanvir Ahmed Bhuiyan	Atiar Rahhan Sunny
ID: 2013-1-55-018	ID: 2013-2-55-014	ID: 2013-2-55-009

Acceptance

This research report presented to the Department of Electronics and Communications Engineering, East West University is submitted in partial fulfillment of the requirement for the degree of B.Sc. in Electronics and Telecommunications Engineering, under complete supervision of the undersigned.

………………………………

Dr. Anup Kumar Paul

Assistant Professor

Department of Electronics and Communications Engineering

Acceptance

This research report presented to the Department of Electronics and Communications Engineering, East West University is submitted in partial fulfillment of the requirement for the degree of B.Sc. in Electronics and Telecommunications Engineering, under complete supervision of the undersigned.

……………………………………….

Dr. M. Mofazzal Hossain

Chairperson

Department of Electronics and Communications Engineering

Acknowledgement

First and foremost with all our heartiest devotion I am grateful to almighty Allah for blessing us with such opportunity of learning and ability to successfully complete the task. A special thanks with honor to our supervisor Dr. Anup Kumar Paul, who was kind enough to allocate his valuable time to provide us with his humble guidance, motivating thought and encouragement.

……………………..

MD.Hasibul Islam Bhuiyan
ID: 2013-1-55-018

……………………..

MD.Tanvir Ahmed Bhuiyan
ID: 2013-2-55-014

……………………..

AtiarRahhan Sunny
ID: 2013-2-55-009

Abstract

The position accuracy of range free localization is a fundamental problem in Wireless Sensor Networks (WSNs). The accuracy of the localization algorithm greatly impacts the performance of the localization dependent protocols and applications, such as routing and storage. Most of the range free localization algorithms are designed by assuming that the sensor nodes are deployed in regular areas without any obstacles. This assumption does not reflect the real-world conditions, especially for outdoor deployment of WSN. In this paper we propose a novel scheme called Range Free Angle Calculation (RFAC) based Sensor Localization in WSNs, which can greatly reduce the localization error in the irregular deployment areas. We estimate the average hop distance by selecting the middle of the transmission path between every two anchor pairs one by one. Then the estimated hop distance is adjusted by the angle between the anchor pairs to that selected middle point. The simulation results show that RFAC achieves significant improvement in localization accuracy in anisotropic WSNs.

Index

Table of Contents Page No

Chapter 1

Introduction

Now-a-days wireless network is a most focusable topic in communication technology.[1,2] Wireless Sensor Networks (WSNs) can be applied in many applications, such as natural resources investigation, Targets tracking, unapproachable places monitoring and so forth. In these applications, the information is collected and transferred by the sensor nodes. Various applications request this sensor nodes location information. Moreover, the location information is also indispensable in geographic routing protocols and clustering [3,4]. All these mentioned above make localization algorithms become one of the most important issues in WSNs researches. Thus, locations of sensor nodes are important for operations in WSNs. The sensor nodes are randomly deployed in inaccessible terrain by the vehicle robots or aircrafts. To be used in many promising applications, such as health surveillance, battle field surveillance, environmental monitoring, coverage, routing, location service, target tracking, and rescue. The Global Positioning System (GPS) or the standalone cellular systems are the most promising and accurate positioning technologies, the limitation of high cost and energy consuming of GPS system makes it impractical to install in every sensor node where the lifetime of a sensor node is very crucial. On the other hand, the cellular signals are interrupted in scenarios with deep shadowing effects. In order to reduce the energy consumption and cost, only a few number of nodes which are called anchor or beacon nodes, contain the GPS modules [4-7].The other nodes could obtain their position information through localization method. Wireless sensor network is composed of a large number of inexpensive nodes that are densely deployed in a region of interests to measure certain phenomenon. The primary objective is to determine the location of the sensor node.

Based on the type of knowledge used in localization, we divide the localization protocols into two categories: range-based and range-free. Range-based protocols use absolute point-to-point distance or angle information to calculate the location between neighboring sensors. The second class of methods, range-free approach, employs to find the distances from the non-anchor nodes to the anchor nodes without any special hardware. Several ranging techniques are possible for range measurement, such as Angle-Of-Arrival (AOA), Received Signal Strength Indicator (RSSI), Time-Of-Arrival (TOA) or Time-Difference-Of Arrival (TDOA) [8-11]. Because of the hardware limitations of WSNs devices, solutions in range-free localization are being pursued as a cost-effective alternative to more expensive range-based approaches.

One way to improve the accuracy of localization would be to rule out distorted path information from some anchors, which however has two particular difficulties. First, because sensors do not have the global view of their network, they have no way of determining which path information is distorted and which is not. Second, anchors can rely on the information that they receive from other anchors that are in an unobstructed straight line path [6-10] because they are able to determine their mutual reliability based on the calculation of an expected hop length.

But anchors and sensors cannot rely on each other in this way because sensors do not know their own locations and so cannot make an expected hop-length calculation. In this paper, we propose a novel range free scheme which we call Range Free Angle Calculation (RFAC) Based Sensor Localization in Wireless Sensor Networks. The proposed method can improve location accuracy without increasing hardware cost of sensor nodes and with few anchor nodes [12,13]. The remainder of this paper is organized as follows. Basic distance measurement techniques for localization in WSNs are described briefly in chapter 2 with their common pitfalls and challenges. Different localization algorithms and their comparative analysis are discussed in chapter 3. We describe various localization based applications in chapter 4. In chapter 5 we present various evaluation criteria for localization. Then we perspective and future challenges in range free localization algorithms in chapter 6. Finally, we conclude in the last chapter.

1.1 Localization

Localization is one of the key techniques in wireless sensor network. The location estimation methods can be classified into target/source localization and node self-localization. In target localization, we mainly introduce the energy-based method. Then we investigate the node self-localization methods. Since the widespread adoption of the wireless sensor network, the localization methods are different in various applications. And there are several challenges in some special scenarios. In this paper, we present a comprehensive survey of these challenges: localization in non-line-of-sight, node selection criteria for localization in energy-constrained network, scheduling the sensor node to optimize the tradeoff between localization performance and energy consumption, cooperative node localization, and localization algorithm in heterogeneous network [14]. Finally, we introduce the evaluation criteria for localization in wireless sensor network.

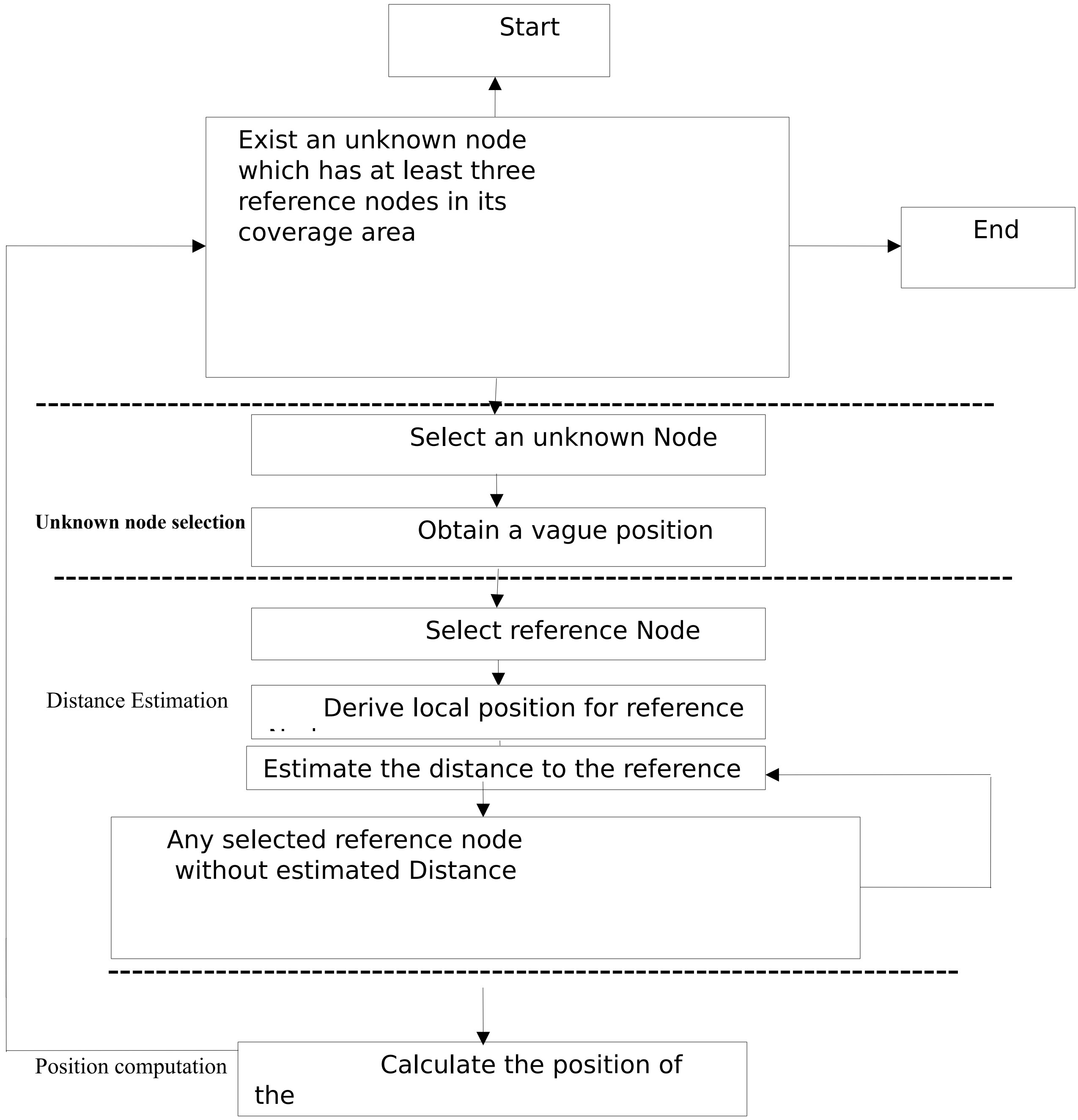
Due to the availability of such low energy cost sensors, microprocessor, and radio frequency circuitry for information transmission, there is a wide and rapid diffusion of wireless sensor network (WSN). Wireless sensor networks that consist of thousands of low-cost sensor nodes have been used in many promising applications such as health surveillance, battle field surveillance, and environmental monitoring [15]. Localization is one of the most important subjects because the location information is typically useful for coverage, deployment, routing, location service, target tracking, and rescue. Hence, location estimation is a significant technical challenge for the researchers. And localization is one of the key techniques in WSN.

Localization Process

The problem of sensor localization is to find out the location of all or subset of sensor nodes. Localization process localizes the sensor nodes based on input data. If there is any anchor available in the network, the common inputs are the location of anchors while other inputs are based on the measurement techniques. The overview of localization process shown in figure 2.

Fig: Localization process

Localization process localizes the nodes on the basis of input data [7]. If any anchor available in the network, the common inputs are the locations of anchors. Other inputs are connectivity information for range free techniques and distance or angle between nodes for range based techniques. The flow sheet of a localization process is shown in figure 3.



Classification of Localization Techniques

There are different possibilities how to divide the computation between sensor nodes and how to choose the localization algorithms. On the basis of computation model [8], the localization techniques can be broadly categorized into centralized and decentralized or distributed techniques. The taxonomy of the localization techniques is shown in figure 4.

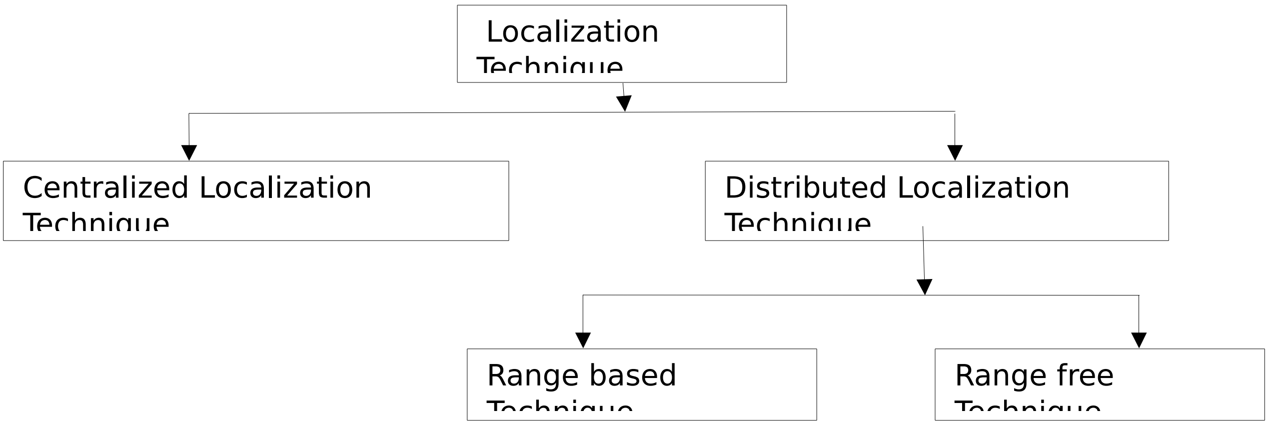


Figure: Taxonomy of localization technique

Centralized Localization Techniques

In the centralized localization all the measurements are collected at central base station (BS),where the computation takes place. After that the results are forwarded back to the nodes. The data transmission in the network causes latency, more consumption of energy and bandwidth. The benefits of this technique are that they eliminate the problem of computation in every node. The drawback of this scheme is lack of ability to access data in proper way as well as inadequate scaling [16]. It is more accessible for small scale networks. Because of existence of global information, it is more accurate than other algorithm. The popular centralized localizations algorithms are: Multi Dimensional Scaling-Mobile Assisted Programming (MDSMAP), Semi Definite Programming (SDP), Simulated Annealing based Localization (LBSA)[17].

Distributed Localization Techniques

In distributed localization sensor nodes perform the required computation themselves and Communicate with each other to get their own location in network. On the basis of range measurements, the distributed localization can be categorized into range based and range free localization techniques. The broad classification of distributed localization techniques is shown in figure 4 [13].

1.2 Range Free Localization Technique

The range free localization techniques have been discussed deeply. In range free schemes, special hardware for distance estimation is not used. So its low cost and simplicity in estimation of distance have attracted the attention of people in recent years.
The taxonomy of range free schemes is shown in [11].

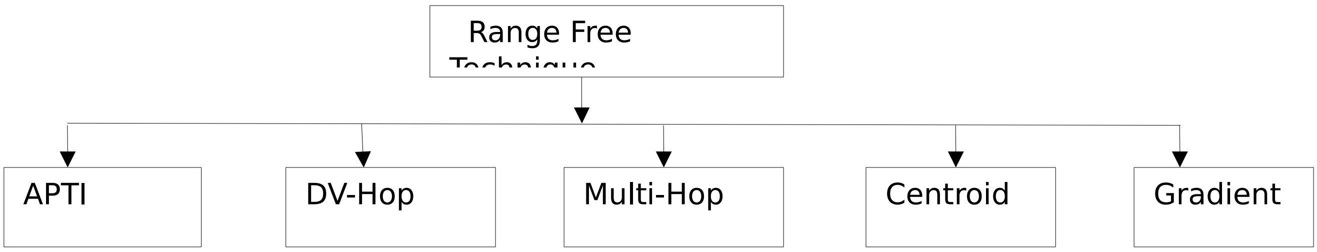


Fig: Taxonomy of localization technique

Approximate Point in Triangle (APIT)

APIT is an area based range free scheme which assumes that some of nodes those are aware of their positions outfitted with high powered transmitters. APIT is located in area to carry out position estimation by separating the area into triangular zones between anchors. Each node’s presence inside or outside the triangle regions allows declining the viable location until and unless every possible sets have reached to an acceptable accuracy. The flowchart representation of APIT algorithm is shown in figure [17].

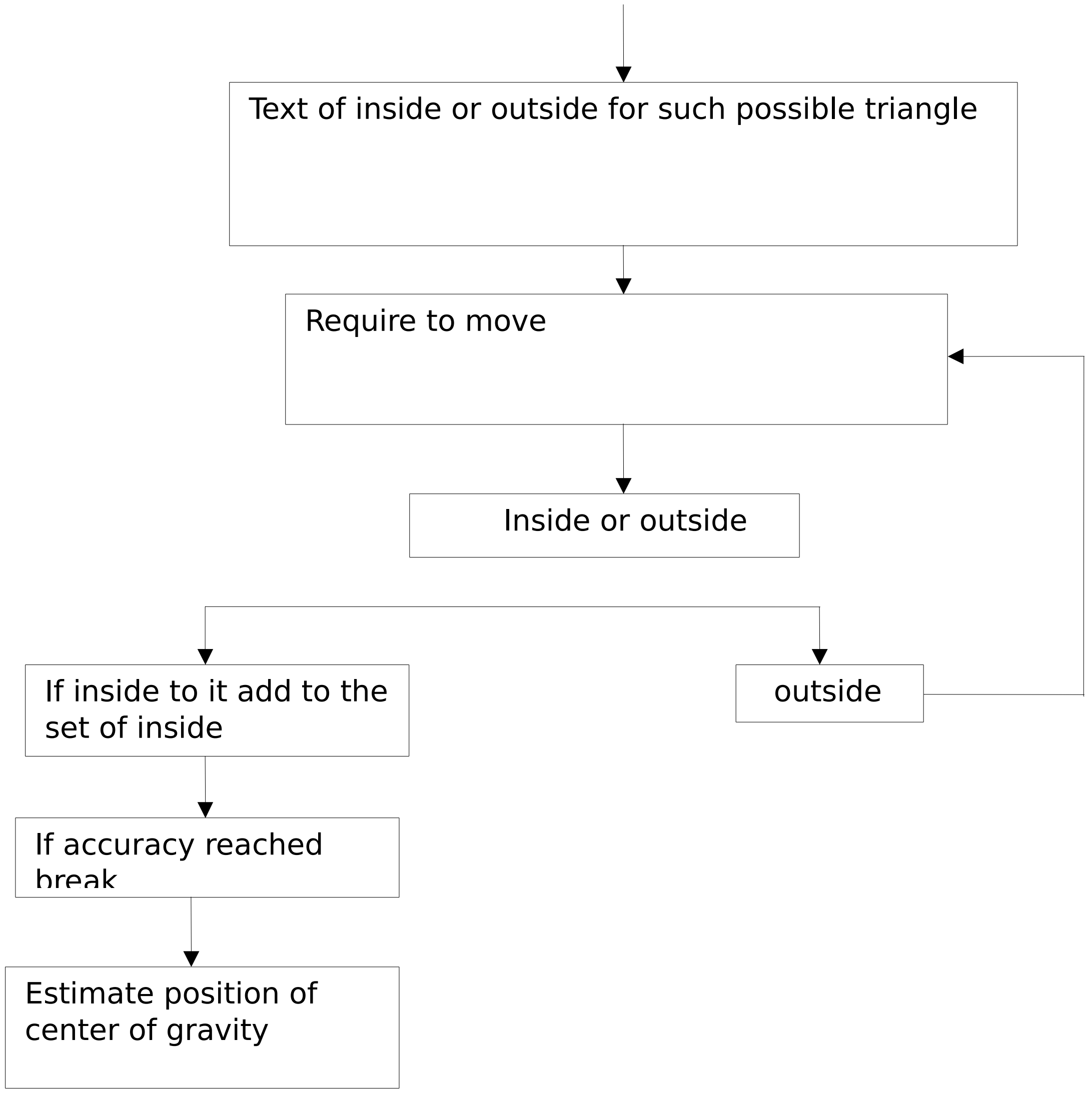


Figure: Flow sheet of APIT Algorithm

DV-Hop

DV-Hop localization uses a mechanism similar to the classical distance vector routing method. One anchor node broadcasts a message which contains the anchors' positions with hop count. Each receiving node keeps the minimum value, which it receives. After that it ignores the other message with higher values. Messages broadcasted out with hop count values incremented at every middle hop. In this scheme, all nodes in the network and other anchors obtain the shortest distance in hops [17-21]. The overall single hop distance in anchor can be computed with the following equation:

$$Hop\ Size_i = \frac{\sum \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum h_j}$$

Where anchor j is at location (xi, yj) and hj is the distance in hops from j to i. anchors propagate the estimated hop size to the closest nodes. The triangulation is used location estimation of unknown nodes [22,23]. In this algorithm for 2 Dimensional deployment of network, minimum 3 anchor's locations are used.

Multi-Hop

Multi Hop techniques are able to compute a connectivity graph. The multi dimensional scaling (MDS) uses connectivity information considering the nodes are within the communication range. This scheme has three steps as follows:

- In the first step, the distance estimation between each viable pair of nodes is done.
- In the second step, MDS is used for deriving the locations to fit the estimated distance.
- Finally, in the last step, optimization is done by putting the known locations into account.

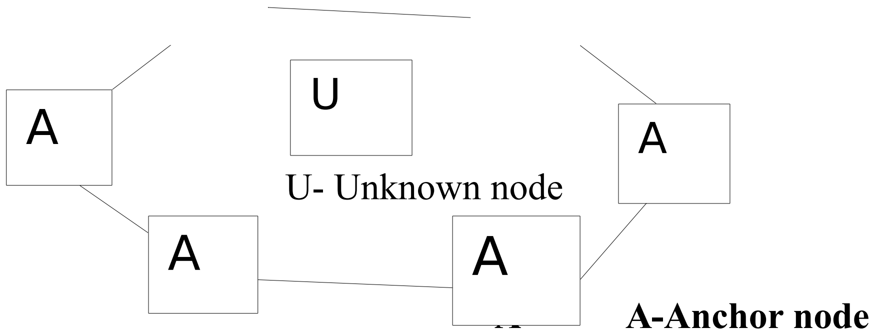
In large scale sensor networks, there are several kind of MDS methods are used such as metric, non metric, classical, weighted [24,25]. The multi hop based multi lateration process allows multi hop nodes to collaborate in finding better position estimates.

Centroid

Centroid scheme uses proximity based grained localization algorithm. In centroid localization algorithm, node's location is computed on the basis of several reference node positions. The centroid localization algorithm uses the location (x_i ,y_i) of anchor nodes (reference node)[26]. After receiving the information, unknown node estimate their position by using following formula:

$$(X_{est}, Y_{est}) = \left(\frac{X_1 + \cdots + X_N}{N}, \frac{Y_1 + \cdots + Y_N}{N} \right)$$

Where (X_{est} ,Y_{est}) indicate the estimation of position of sensor node and N is the number of anchor nodes. The task of centroid algorithm is to take a number of nodes around the unknown nodes as shown in figure [27].



Gradient

In gradient algorithm, unknown nodes obtain their locations through multi lateration. It also uses hop count which is initially set to zero and incremented as it propagates to other nearby nodes. Gradient algorithm follows certain steps such as the following:

- In the first step, anchor nodes broadcasts a message containing its coordinated and hop count value.
- In the second step, unknown node determines the shortest path between itself and anchor node from which it receives beacon message [28].The estimated distance can be calculated by following equation:

$$d_{ji} = h_{j,Ai}\, d_{hop}$$

In the third step, minimum error in which node calculates its coordinate is computed by following equation:

$$E_j = \sum_{i=1}^{n} d_{ji} - d^{ji}$$

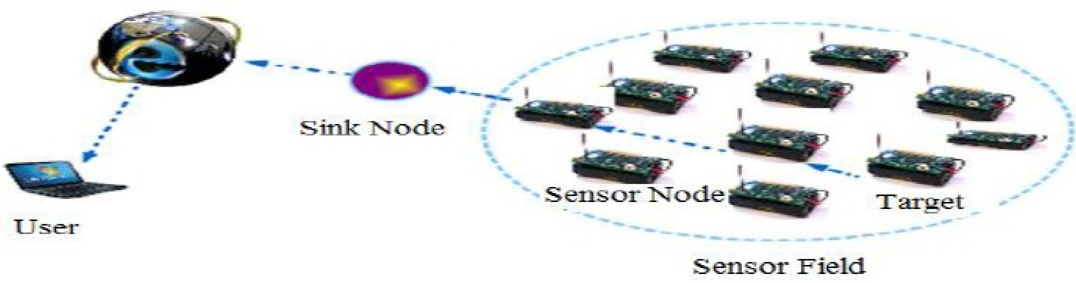
Where d_{ji} is gradient propagation based estimated distance.

1.2 Wireless Sensor Network (WSN)

Wireless communication technology has enabled the growth of comparatively economical and low power sensors. The general goal is to make wireless sensor network that is capable to sense the surroundings, compute some task and communicate with each other to attain some objective like monitoring some phenomenon, target tracking, forest fire detection, and battlefield surveillance. In the majority of the applications, location information of each node in the network is needed [28]. However, in a large amount of cases, sensor nodes are deployed randomly right through some region. Thus, the first task is to find out the location of the nodes.

To find out the physical location of sensor node in WSN operation is crucial problem because of its use in
(i) identification of the origin of sensor reading,
(ii) energy aware geographic routing,
(iii) self organization and self configuration of networks [29].

Apart from the above, in various applications the location itself is information of interest. There is one easy way i.e. manual configuration but this is impractical in large scale deployment. Simple wireless sensor network is shown in figure [30].



The other possible way for node localization is to add Global Positioning System (GPS) to sensor node [3].However, adding a GPS receiver to each node is not viable solution because of its large power consumption, high cost, and imprecision [3], [4]. In the literature, numbers of localization system and algorithms for sensor network have been reported, which are broadly classified into range based and range free schemes on the basis of location estimation mechanism. The range based schemes are defined by protocols that use absolute distance estimates for the location computation. The range free schemes make no assumptions about the accessibility or legality of such information [5]. Due to hardware restrictions of sensors, solutions in range free schemes are being considered as cost effective substitute to the most expensive range based schemes. The taxonomy of the localization algorithms based on several distinct criteria such as: dependency of range measurements; computational model; anchor.

1.3 Importance in Localization Techniques

Sensor network localization is an active research area and has numerous issues so still has a lot of scope for research community. Some of the issues need to be addressed are:

- **Cost effective algorithms**: During the design of localization algorithm, designer must keep in mind the cost incurred in hardware and deployment. GPS is not suitable because of its cost and size of hardware.
- **Robust algorithms for mobile sensor networks:** Mobile sensors are much useful in some environments because of mobility and coverage facility. Hence, development of new algorithms is needed to accommodate these mobile nodes.
- **Algorithms for 3 Dimensional spaces:** For many WSN applications, accurate location information is crucial. The more of the proposed algorithms are applicable to 2D space. Some of the application needs 3 D [30-32] positioning of WSNs.

Chapter 2

Localization Measurement Techniques in WSNs

2.1 Angle of Arrival (AOA) Measurements

The AOA measurement techniques are also known as the bearing measurements or the direction of arrival measurements. The AOA measurements can be obtained from two categories of techniques:

One from the receiver antenna's amplitude response and another from the receiver antenna's phase response. These techniques calculate the angle at which the signal arrives from the anchor node to the unknown sensor nodes. Then, the region where the unknown sensor is located is a line having a certain angle from the anchor node. In AOA measurement techniques, at least two anchor nodes are needed to calculate the position[33-35]. The localization error could be large if there is a small error in measurement. The accuracy is depended on the directionality of the antenna and measurements are further complicated by the presence of shadowing and multipath effect of the measurement environment. A multipath component from the transmitted signal may appear as a signal coming from entirely different direction and consequently causes a very large error in measurement accuracy [50].

Thus, AOA technique is of limited interest in localization unless it is used with large antenna arrays [8].

As a result, for WSNs with tiny sensor nodes, this option is not energy efficient at all.

2.2 Distance Related Measurement

Distance related measurements can be further classified as propagation time measurements (one way, round trip and time difference of arrival (TDOA)) [34], RSS based and connectivity based measurements.

2.2.1. Propagation Time Measurement

In **one way propagation time measurement**, the principle approach is to measure the difference between the sending time of the transmitting signal and the receiving time of the signal at the receiver. The distance between the transmitter and the receiver is then computed using this time difference and the propagation speed of the signal in the media. Time delay measurement is a relatively mature field[35,36]. However, a major limitation in implementing the one way propagation time measurement is that, it requires the synchronization between the local time at the transmitter and the local time at the receiver[37]. Any difference between the local times at the transmitter and the receiver will cause large error in estimating distance and consequently the position estimation error will be large. At the speed of light, a very small synchronization error of 1 ns will translate into a distance measurement error of 0.3 m [50]. The accurate synchronization requirement may add extra cost to the sensor nodes,

by demanding a highly accurate clock or may add complexity to the sensor network by demanding a sophisticated synchronization algorithm. This disadvantage makes this option less attractive [38,39] for WSNs localization.

Round trip propagation time measurement measures the difference between the times when a signal sent by a sensor node is returned from the second sensor node to the first sensor node.

In this technique, there is no need for time synchronization, since the time difference is measured at the transmitting sensor node using the same local clock. The major source of error in this technique is the delay required in the second sensor node to handle the signal [40,41], process it and send back again.

This internal delay is either known via a priori calibration or measured at the second sensor node and send back to the first sensor node where it is subtracted. In addition to the synchronization problem, both one way and round trip propagation time measurements are affected by noise, signal bandwidth, non line-of-sight and multipath environment. To overcome some of the limitations, Ultra Wide Band(UWB) signals have been used for accurate propagation time measurements [51]. UWB can achieve very high accuracy because its bandwidth is very large and therefore its pulse has a very short duration.

This feature makes fine time resolution of UWB signals and therefore the separation of multipath signals possible [42].

Time difference of arrival measurement measures the difference between the arrival times of a transmitting signal at two separate receivers respectively, assuming the locations of the two receivers are known and they are perfectly synchronized [43]. This technique requires three receivers to uniquely locate the transmitter location. The accuracy is affected by synchronization error and multipath [44].

The accuracy improves when the distance between receivers are increased because this increases the difference between the times of arrival [43,44].

2.2.2. Received Signal Strength (RSS) Based Measurement

Received signal strength measurement estimates the distance between two sensor nodes from the received signal strength of the signal. Most sensors have the capability to measure the RSS. The distance estimated from the RSS is a monotonically decreasing function[45]. The relation is modeled by the following log-normal model:

$$P_r(d)[dBm] = P_0(d_0)[dBm] - 10n_p log_{10}\left(\frac{d}{d_0}\right) + X_\sigma$$

where $P_0(d_0)$ [dBm] is a reference power in dB mill watts at a reference distance d0 from the transmitter, n_p is the path loss exponent that measures the rate at which the received signal strength decreases with the distance, $X\alpha$a zero mean Gaussian random variable with standard deviation s and it accounts for the random effect caused by shadowing. Both n_p and s are environment dependent. Given the model and the model parameters, which are known via a priori measurements, the distance between two sensor nodes can be obtained from the RSS measurements. Localization algorithm can then be applied to use this distance and estimate the position using multi lateration technique [46-48].

Another interesting technique to measure distance between an optical transmitter and an optical receiver is the lighthouse approach. In this approach, the distance is measured by estimating the time duration that the receiver dwells in the optical beam. The advantage is that the optical receiver is of small size and low cost [49]. However, it requires line of sight between the transmitter and the receiver.

2.2.3. Connectivity Based

Connectivity based measurement is the simplest form of all the measurement techniques we have discussed so far. In this technique, a sensor is connected to another sensor if it is within the radio transmission radius of each other. Such measurement technique is treated as the binary measurement [9].

In this technique, a sensor node is connected to another sensor node (binary 1) or not connected directly if it is outside the radio transmission range (binary 0). From one sensor to anther sensor, the distance is thus represented as the hop count and various algorithms are applied to measure the average hop distance as accurately as possible [14,50]. This category of WSNs localization algorithm is popularly known as the range free localization algorithm.

2.3. RSS Profiling Measurement

RSS based measurement estimates the distance between sensor nodes as was discussed in the previous section. The localization algorithms then use this distance to calculate the position of the sensor nodes. However, the implementation of this kind of algorithm faces two major challenges: first, the wireless environments, especially the indoor wireless environments and the outdoor wireless environments with irregular objects inside the measurement area, make the distance estimation from RSS very difficult. In addition, second, the determination of model parameter is also a very difficult task. To overcome such difficulties, RSS profiling measurement techniques [55–58] that estimate sensor location from the map of RSS measurements are used to improve the accuracy.

The RSS profiling measurement works by first constructing a form of map of signal strength of anchor nodes at different locations of the measurement area. The map is obtained either offline via a priori measurements or online by deploying some sniffing devices [56] at some known locations. This kind of technique is mainly used for WLAN, but they would appear to be attractive for WSNs too [50].

In RSS profiling based localization systems, in addition to anchor nodes and unknown sensor nodes, a large number of sample points, e.g., sniffing devices [56] or reference points are distributed throughout the coverage area. At each sample point, the RSS signal strength is obtained from different anchor nodes, where nth entry corresponds to the nth anchor nodes. Obviously, different entries have different signal strength and many of them have zero values or near to zero values due to the large distance from the anchor nodes.

Chapter 3

Localization Algorithms in WSNs

Based on the measurement of inter-sensor distance, localization algorithms in WSNs can be broadly classified into two categories: centralized and distributed [50]. In centralized localization technique, all the inter-sensor measured distances are sent to the central location where the positions of each and every sensor node are calculated. On the other hand, in distributed localization technique, the individual sensor nodes calculate their own position by utilizing the distance measurement from other anchor nodes. Major approaches for designing centralized algorithms are Multi Dimensional Scaling (MDS) [59], linear programming [60] and stochastic optimization algorithms [61,62]. Some well known distributed localization algorithms are DV-Hop [52],DV-Distance [14] and a number of other algorithms based on the above two algorithms [17,18,63].Centralized and distributed localization algorithms are further subdivided into range based and range free algorithm. Moreover, fusing the information from different positioning systems with different physical principles can improve the accuracy and robustness of the overall system. This leads to the development of another category known as hybrid data fusion [8].

Range based localization technique utilizes the measurement techniques such as AOA, TOA, TDOA and RSSI as is discussed in the previous section to estimate the distance between sensor nodes and then calculates the position [37]. Range based technique usually achieves high ranging accuracy but requires extra hardware and consumes more energy. In the following sub-section, we focus on range free localization and hybrid data fusion techniques.

3.1 Range Free Localization Algorithm

Range free localization technique, which is totally dependent on the contents of the received packet and is a much cheaper solution than many range based localization techniques [64] in WSNs.

Range free schemes are simple, inexpensive and energy efficient where localization is performed using geometric interpretation, constraint minimization and resident area formation [65].

3.1.1. Analytical Geometry Based

Most popular alternatives suitable for range free localization algorithms are based on analytical algorithms which evaluate theoretically the average hop distance of the network using the statistical characteristics of the network deployment. The obtained average hop distance is locally computable [66] at each sensor node and likewise other range free method, it has to be broadcasted to other sensor nodes.

To cope with the problem of anisotropy in a network, pattern driven localization scheme is proposed. For anisotropic environment, this paper devised two methods to calculate the estimated distance between anchors and sensors based on whether the anchor is slightly detoured or strongly detoured from normal sensor nodes [67]. For slightly detoured anchors, it utilizes the information from the nearest anchors (namely reference station) and this reference station must be within three or four hops away from normal sensor nodes. Which means that, the anchors distribution density must be very high [68]? It devised one method to discard the strongly detoured anchors. However, no indication of how many anchors fall in the strongly detoured category because it may be impossible to accurately determine which anchors are slightly detoured and which are moderately or strongly detoured [69]. Another analytical algorithm argues that average hop distance and number of hops between anchor and sensor nodes are not sufficient to calculate accurate position [70]of the sensor nodes. It also depends on number of forwarding nodes (which forward any data between two nodes). By utilizing this information along with other information, the author in showed that further accuracy can be achieved.

3.1.2. Mobile Anchor Based

In this technique, a mobile anchor with GPS capability moves into a sensing area and periodically broadcast its current geometric coordinates. The other sensor nodes collect the location coordinates of the mobile anchor node. Later, the sensor nodes choose three non-collinear coordinate points of the mobile anchor node and apply different mechanisms to estimate position[71]. Based on this principle, several localization algorithms are devised.

The author in proposed a geometric conjecture (perpendicular bisector of the chord of a virtual circle) based range free localization algorithm, where a mobile anchor traverses a sensing area and periodically broadcasts its current location coordinates. The neighboring sensor nodes keep track of entering and departing anchor coordinate points to construct a chord on its communication range. The sensor node repeats this process until it gets at least three coordinate points from the moving anchor node on its communication range. The line segments between these three selected coordinate points create two chords on its communication range [72,73]. Later, the perpendicular bisector of the two cords gives the position estimates of the sensor nodes. To further improve the localization accuracy, the author in proposed a geometric constraint based localization scheme. In this scheme, the selection process of the three anchor coordinate points on the communication range of the sensor node remains the same as in. Initially, the intersection of the selected two anchor coordinate points determines the constraint area of the sensor node [74-76]. This process is repeated with another two intersected points to further narrow down the constraint area of the sensor node.

Finally, the average of all the intersection points gives the position estimates of the sensor node. Another approach [75] proposed a constraint area based localization using mobile anchor. In this approach, the specific type of moving anchor's trajectories creates a specific type of constraint areas for the sensor node. To identify the potential location of the sensor node within different constraint areas, a number of intersections are created within different constraint areas until the final arrival of the coordinate points before the final departure of the anchor node [76]. Each intersection further narrow downs the potential location of the sensor node within the overlapping constraint areas.

However, the scheme shows high localization error when random waypoint mobility model is used for the moving anchor node. Also the scheme is computationally expensive due to multiple intersection computation [77]. Another approach proposed a curve fitting method along with a mobile anchor node to calculate the location of the sensor node. In this approach, the arrival and departed coordinate points of the moving anchor nodes are recorded and this is repeated as many times as the moving anchor re-enters the communication region of the sensor node. The localization begins through fitting a curve on the few selected coordinate points on communication range and iteratively refined through Gauss-Newton method. The center coordinates of the fitted curve define the position of the sensor node [78]. Mobile anchor based localization is proposed in, where the localization begins with approximation of the geometric arc parameters. The approximated arc parameters are used to generate the chord on the virtual circle. Later, the perpendicular bisector of the chords along with the approximated radius is used to estimate the position [79] of the sensor node. The accuracy is improved for boundary nodes too.

Although several techniques are devised so far, a common pitfall to all mobile anchors based localization schemes arise when considering the longer periodic interval of the message send by the anchor node and the irregular radio propagation pattern [70].

DV HOP Count Algorithm

Almost all the range free localization techniques mainly use hop count based information to calculate the position. DV-Hop [52] and Centroid [36] are the pioneering approaches of this type.
Centroid is designed for sensor nodes which have at least three neighbor anchor nodes. Assume that the sensor node N has three neighbor anchors A1, A2, A3, whose coordinates are (x1, y1), (x2, y2),and (x3, y3), and all nodes have equal communication range. The principle of Centroid is to regard the central point N centroid of anchors as the estimated position. The position of Ncentroid, denoted as (X centroid, Y centroid) could be calculated [80-83] as (x centroid, y centroid) = ((x1 + x2 + x3)/3, (y1 + y2 +y3)/3.

Centroid has very low communication and computation cost, and can get relatively good accuracy when the distribution of anchors is regular. However, when the distribution of anchors is not even, the estimated position derived from the Centroid algorithm will be inaccurate [84,85]. On the other hand, the hop count based method DV-Hop and hop-terrain requires small number of anchors.

DV-Hop plays an essential role in many localization methods to give primal distance estimation from sensor nodes to anchor nodes [86]. DV-Hop propagates distance estimation among anchor nodes represented by number of hops throughout a WSN. Anchor nodes can then estimate the average distance of each hop, with which each sensor node calculates its estimated distances [87] to anchor nodes.

By multi lateration, the location is then calculated as follows:

Let (x, y) be the unknown node D_0s location and (x_i, y_i) be the known location of the I_oth anchor node receiver. Let’s say the i0th anchor node distance to unknown nodes are di and the total number of anchors deployed in the network is n. Then, here is the following formula for calculating location [88] in range free localization.

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2} & = d_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2} & = d_2 \\ \vdots & \vdots \\ \sqrt{(x-x_i)^2+(y-y_i)^2} & = d_i \end{cases}$$

$$A = -2 \times \begin{pmatrix} x_1 - x_n & y_1 - y_n \\ x_2 - x_n & y_2 - y_n \\ \vdots & \vdots \\ x_{n-1} - x_n & y_{n-1} - y_n \end{pmatrix}$$

Where, $P=(A^TA)^{-1}A^TB$

However, DV-Hop requires not only uniformly deployed WSNs but also the same attenuation of signal strength in all directions [62-65]. To modify the disadvantage of existing DV-Hop localization algorithm, the relevant literature proposed many improved algorithms based on the following metric:

Improvement based on average hop distance:

In the randomly deployed node density and connectivity of the network, there are many works that modified the average hop distance between anchor nodes to improve the position estimation accuracy [67–70]. Such as [67], it improved the location accuracy by modifying the network average hop distance based on minimum mean square error criteria as Hop Size Name the coordinates of anchor nodes I and j and h_{ij} is the number of hops between anchors I and j. The algorithms [67,68], made improvements on distance estimation and consequently the accuracy of the DV-Hop algorithm.

Improvement based on node information and nearest anchors:

There are still some disadvantages in the improved algorithms that are based on the average hop distance, such as no obvious improvement on localization accuracy, especially when the transmission route is not straight but detoured. These approaches are accurate insofar only when the topology is isotropic, i.e., shortest paths between anchors and sensors approximate to their Euclidean distances [70]. However, there may be large errors in the distance estimates if the topology is not isotropic or contains a hole (anisotropic environment) [71]. Therefore, some modified methods were proposed using the anchor node information and the relationship between anchor node and sensor node or topological structure information to improve the DV-Hop localization method. In order to alleviate the influence of holes (obstacle shape), Shang et al. [72] suggest using only four nearest anchors, assuming that the shortest paths to the nearest anchors may be less affected by irregularities, and this does produce good results in some cases but with a drawback of the possibility to falsely discard some good anchors which can improve the localization accuracy.

Improved DV-HOP Algorithm

In this subsection, we improve DV-Hop algorithm focus on step 2 and step 3.

In step 2, after obtained the hop-size, anchor node broadcasts its hop-size to network as a correction. The format of the package is {Id, Hop-Size i}, including the identifier id, an average size for one hop Hop-Sizei [89-90]. Once a node gets the package, it adds the information to a table and also broadcasts it to neighbor nodes. The package for iterative ID will be dropped. After the step 1 for broadcast, all of the nodes get the Hop-Sizei, which calculated by the anchor nodes in the first step of DV-Hop algorithm [91]. We average whole of the hop-size of different anchor nodes using the following formula:

$$HopSize_{ave} = \frac{\sum HopSize_i}{n}$$

where n is the number of anchor nodes, Hop $Size_{(i)}$ is obtained using (3-1). In the end of this step, unknown nodes compute the distance to the beacon nodes based hop-length and hops to the beacon nodes [92] by the formula:

$$d_i = hops \times HopSize_{ave}$$

In step 3, a general model for two-dimensional (2-D) position location estimation of a source using M anchor nodes is developed. Let (x, y)be the source node location and (x_i, y_i) be the known location of the i'th anchor node receiver Denote the distance[90] between the unknown node and anchor node I by d_i. It is clear that

$$d_i = \sqrt{(X_i - x)^2 + (Y_i - y)^2}$$

In DV-Hop algorithm, the estimated physical distances are used together with the anchor positions to perform a triangulation in order to get the final localization results. In our improved DV-Hop localization system, we will not adopt traditional Triangulation algorithm but use 2-D Hyperbolic location algorithm [90][102].So we propose to use a least square method to give a good estimation of such a starting point [102].

By the definition of (30-34), we have the following expression:

$$X_i^2 + Y_i^2 - 2X_i x - 2Y_i y + x^2 + y^2 = d_i^2 \Rightarrow$$

$$d_i^2 - E_i = -2X_i x - 2Y_i y + K$$

where $E_i = X_i^2 + Y_i^2$, $K = x^2 + y^2$.

Let $Z_c = [x, y, K]^T$,

$$G_c = \begin{bmatrix} -2X_1 & -2Y_1 & 1 \\ -2X_2 & -2Y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2X_i & -2Y_i & 1 \end{bmatrix},$$

And

$$h_c = \begin{bmatrix} d_1^2 - E_1 \\ d_2^2 - E_2 \\ \vdots \\ d_i^2 - E_i \end{bmatrix},$$

we can have

$$G_c Z_c = h_c$$

Using Least Square (LS) algorithm we can get

$$Z_c = (G_c^T G_c)^{-1} G_c^T h_c$$

Then, the coordinates of the unknown node, (x,y) is expressed as:

$$\begin{cases} x &= Z_c(1), \\ y &= Z_c(2). \end{cases}$$

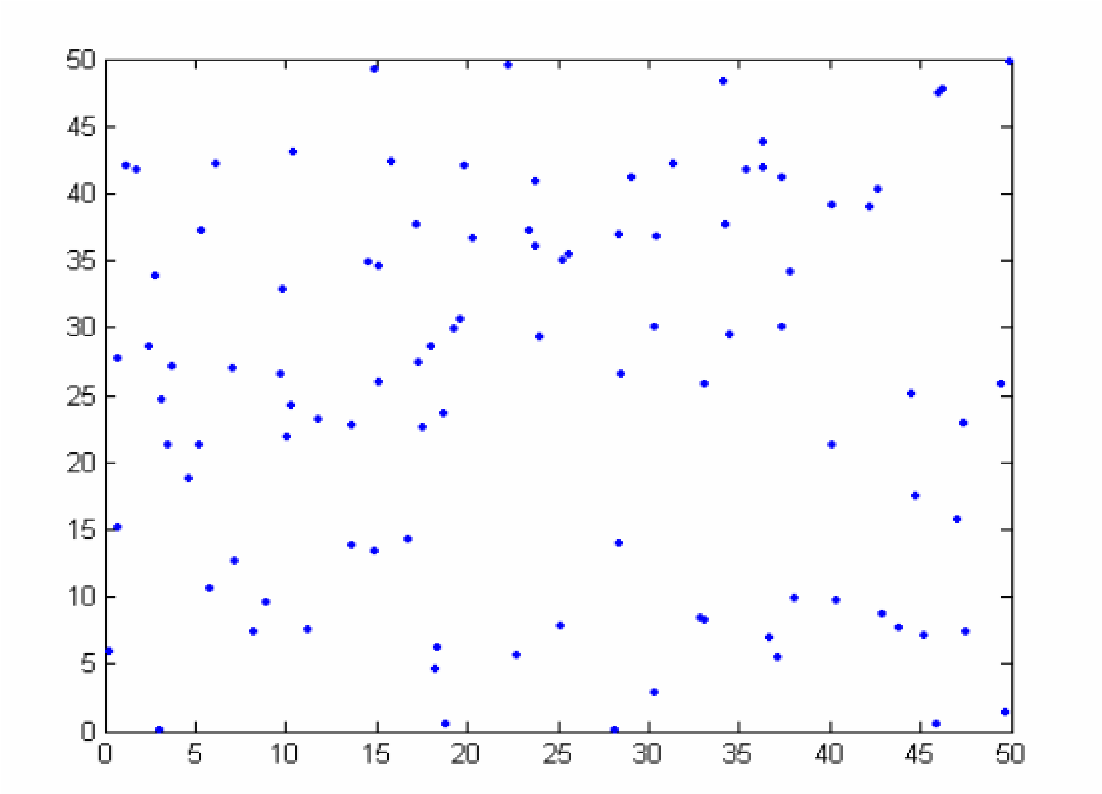


Figure: Nodes distribution

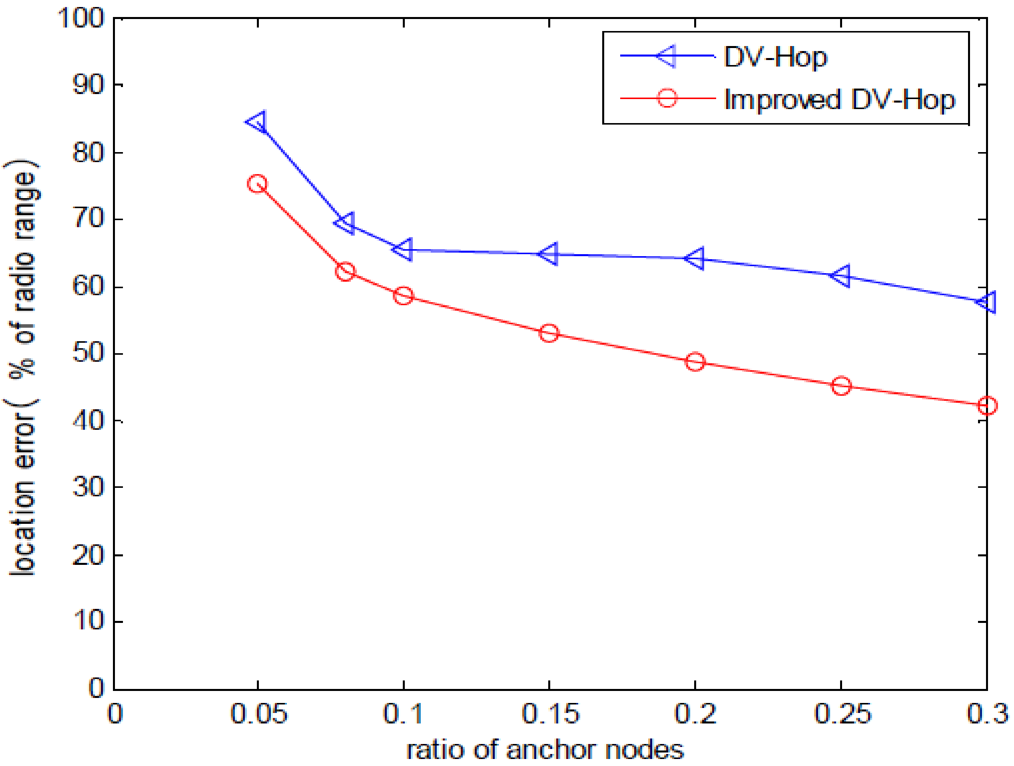


Figure: Location error

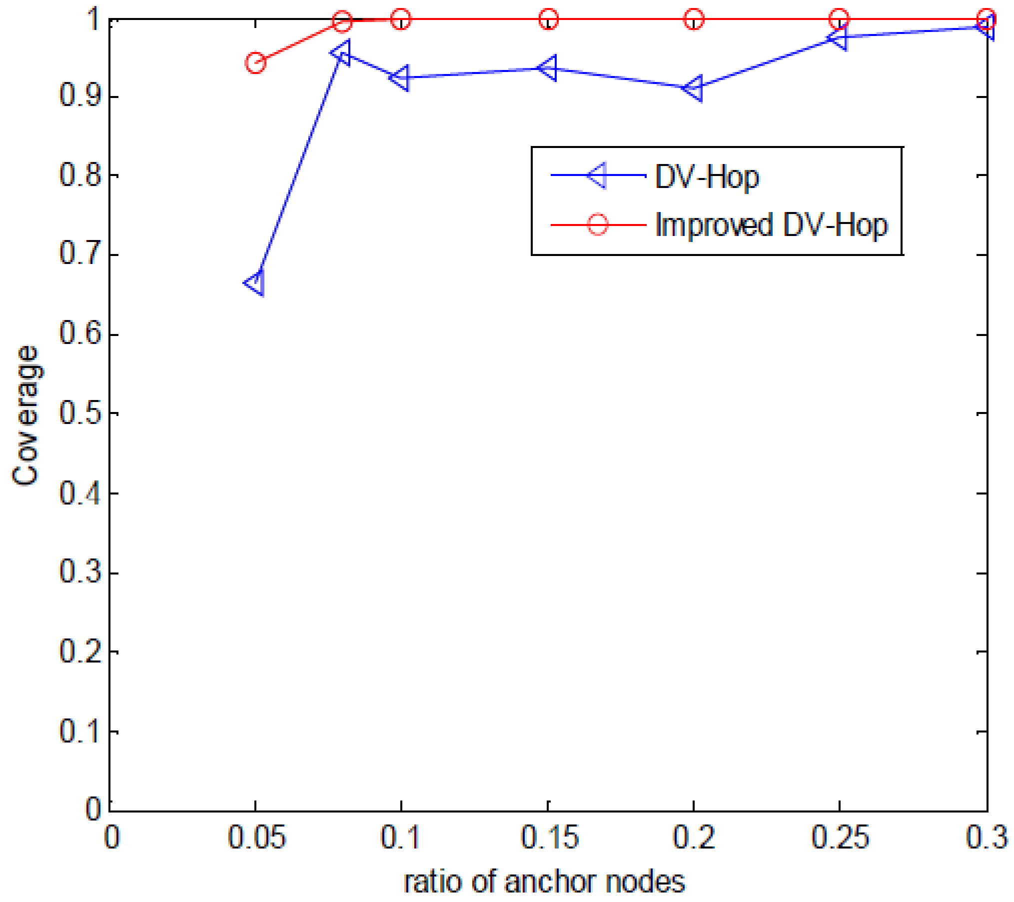


Figure: Location coverage

3.2.1 Differential Evolution Algorithm (DE)

To every min F (x) minimization problem, DE algorithm is based on the populations ti these populations exist N candidate solutions, 1,2,...,i N , is the population, t is the current generation. In the mutation operation, each random vector are obtained by the equation (4), r is random numbers that ranges from 1 to N , F represents a weighting factor that ranges from 0 to 2 [90-93].

$$\mathbf{V_i^{t}=X_{r1}^t+F(X_{r2}^t-X_{r3}^t)}$$

In the hybrid operation, we use the two vectors to obtain the new population

$x_i^{t'} = [x_{i1}', x_{i2}', \ldots, x_{iD}']$, including the random vector $v_i^t = [v_{i1}, v_{i2}, \ldots, v_{iD}]$ and target vector

$x_i^t = [x_{i1}, x_{i2}, \ldots, x_{iD}]$

$$x_{ij}' = \begin{cases} v_{ij}, if\ randb(j) \le C, R\ or\ j = randr(i) \\ x_{ij}, if\ randb(j) \ge CR\ or\ j \ne randr(i) \end{cases}$$

where randb (j) ≥[0.1], j €[1,D]represents the *j-th* value in the generated random numbers.*CR*€[0.1] , *CR* represents the probability mutation randr (i) € [1,2,…,D], randr(i) gets the index randomly[94-96]. It's function is to ensure ' $x_i{}'$can get not less than one parameters from v_i^t. Select operation uses the greedy strategy:

$$x_i^{t+1} = \begin{cases} x_i^{t'}, if\ \varphi(x_i^{t'}) \prec \varphi(x_i^t) \\ x_i^t,\ \text{otherwise} \end{cases}$$

where $\varphi(x)$ represents the fitness function.

3.3. Hybrid Data Fusion

Hybrid data fusion is based on the principle of fusing the information from different positioning systems with different physical measurement techniques in order to achieve higher accuracy as compared to other stand-alone localization techniques. Recently, research work has been focusing on two main approaches in hybrid data fusion: centralized and distributed. Iterative positioning [77–79] and cooperative link selection [80,81] are used with the distributed approach. In iterative multi lateration, once the position is estimated for unknown nodes, this node is used as the anchor node for other unknown sensor nodes. Multiple iterations are needed to complete the localization process.

Another interesting work [82] utilizes the technique of combining angle based localization, map filtering, and pedestrian dead reckoning (PDR) where absolute position estimates are provided by the angle based localization techniques. Pedestrian dead reckoning provides accurate length and shape of the traversed route. Thus, the estimates obtained from angle based localization techniques and the PDR movement are merged together with a vector map built in a particle filter is used as the fusion filter [83]. Hence, merging different information from different positioning techniques lead to higher positioning accuracy.

Hybrid data fusion is also used for the purpose of pedestrian tracking. Usually, this hybrid technique merges inertial measurement and RSS information via a Kalman filter. Classic hybrid methods [84,85] were based on fingerprinting RSS method or map based method. On the other hand, another method [83] uses a channel modeling technique, where a propagation channel model gives a direct relation between the distance of two nodes and the RSS. Then, triangulation or multi lateration is utilized to estimate the node position from a set of distances to some known anchor nodes. This approach has minimal calibration cost. Additionally, fusion between inertial measurements and channel based localization provides higher accuracy as compared to finger printing based methods.

Another hybrid data fusion system is achieved by merging the information from WLAN with the build-in camera on a smart phone for position estimation [86]. This approach utilizes visual markers pre-installed on the floor for the position correction. Visual information is combined also with the radio data to track a person wearing a tag using a mobile robot in indoor environments. The author in presented a method to integrate range-based sensors and ID sensors[87,88] (i.e., infrared or ultrasound badge sensors) using a particle filter to track people in a networked sensor environment. As a result, their approach is able to track people and determine their identities owing to the advantages of both sensors.

Another method is based on the fusion of video and compass data acquired by the anchor node [89]. This method calculates the anchor node location by using a digital compass (magnetometer),an image taken by a video camera and the exact location data for some geographically-located referential objects (e.g., solitary trees, electricity transmission towers, furnace chimneys, etc.) situated in the deployment area[90]. This method, due to the low price of digital compasses, is particularly suitable for video-based or multimedia-based WSNs, where the nodes already equipped with digital compasses may simply become anchor nodes [91] or anytime the GPS receiver is not considered to be an appropriate solution.

The author in developed a hybrid localization system in WSNs, which is composed of coarse-grained localization system and fine-grained localization system. The coarse-grained localization system takes the wireless signal strength as the reference for distance and gets the rough region as the unknown node [92]. The fine-grained localization system is in charge of location refinement that takes image to localize the unknown node with camera sensor nodes.

Hence, different kinds of information fusion lead to an improvement in the positioning accuracy, usually at the cost of additional complexity. For instance, data fusion occurs also with different types of RF sensors to improve the localization accuracy since different positioning systems may complement each other.

3.4 Comparative Performance of Centralized and Distributed Localization Algorithms

Centralized and distributed algorithms can be compared from several perspectives including, location estimation accuracy, implementation and computational complexity, and energy efficiency.

Distributed localization algorithms as compared to the centralized algorithms are considered to be more computationally efficient and can be easily implemented in a large scale WSN. However, in certain network types, where centralized information collection architecture already exists, such as health monitoring, precision agriculture monitoring, environment monitoring, road traffic control network etc [27], the measurement data from individual sensor node needs to be collected and processed centrally.

In such a network, the individual sensor nodes have limited processing capability for saving energy; the localization related data can be piggybacked with other monitoring data and send back to the central processing node [29]. Therefore, a centralized processing algorithm is more convenient in such situations than distributed algorithm with existing centralized architecture.

While considering the estimation accuracy of localization algorithms, centralized algorithms provide more accurate estimation results than distributed algorithms. One of the key reasons behind this is that, centralized algorithms have global view of the network. However, centralized algorithms[47] suffer from scalability problems and are not suitable at all for large scale sensor network. Other drawbacks of centralized algorithms as compared to distributed algorithms are their higher computational complexities, unreliability due to the inaccurate accumulated information (loss of information may occur over multi hop) collected from multi hop sensor nodes to the central node in WSNs.

On the other hand, while considering design complexity, distributed algorithms are more difficult to design than centralized algorithms, due to the complexity[33] of local behavior and global behavior. That is, a distributed algorithm which works locally optimal may not behave equally optimal globally and is an open research problem. Error in distance estimation between sensor nodes propagated to other nodes which further deteriorate the estimation accuracy of the distributed algorithm [31-33]. Moreover, distributed algorithms require a number of iterations to arrive at a stable solution.

This may take longer time for a localization algorithm than the acceptable in some applications. From the perspective of the energy consumption, the energy needed for specific type of operation (processing, transmitting, and receiving) in the specific hardware and the setting of the transmission range needs to be considered in centralized and distributed algorithms. Depending on the setting, it is seen that the energy required to transmit a single bit could be used to process 1000–2000 instructions [47]. Centralized algorithms require each sensor to send the localization related information over multi hop to the central node where as distributed algorithms require only local exchange of information within single hop (between neighboring nodes). However, in distributed algorithms, many such information exchanges (iterations) are required among sensor nodes to arrive at a stable solution. A comparative research about the energy efficiency of centralized and distributed algorithms are presented, where the author concluded that in distributed algorithms[30-34], the number of iterations needed to arrive at a stable solution do not exceed the number of hops to the central processor, then distributed algorithms are more energy efficient as compared to the centralized algorithms[35].It is worth noting that the differences between centralized and distributed algorithms are sometimes ambiguous. Any distributed algorithms can be applied to centralized manner. In addition, distributed versions of centralized algorithms can also be designed for certain applications.

A typical way of designing distributed versions of centralized algorithms would be to divide the total network area into small areas, where in each area the centralized algorithms will be applied and then collecting the areas final result through the overlapping [39]sensor nodes from each area and stitching these sensor nodes to obtain a global map. Such algorithms may offer optimal tradeoff between the merits and demerits of centralized and distributed algorithms.

Chapter 4:

Localization Based Applications

Positioning and navigation for mobile devices is a booming market with expected size of 4 billion dollar in 2018. A reliable, user friendly, and accurate position information in navigation for mobile user might open the door for many promising applications and the creation of new business opportunities. It is thus considered to be a cornerstone in realization of Internet of Things (IoT) vision [1].

Location based services:

Location based services provide spatial information to the end users through wireless networks and/or the Internet. Applications that provide location based services can offer the context and the connectivity needed to dynamically associate the position of a user to context sensitive information about current environments. Location based services send data by knowing the geographical location [41] accessed by a mobile user. Thus, this service is very essential both in indoor and outdoor environment. For example, indoor applications with location based services can provide safety information, up to date cinemas, events or concerts in the vicinity. Moreover, application of this type includes navigation application to direct the user to the place of interest [46]. Location based services are also used for advertisement, billing, and for personal navigation to guide guests of trade-shows to the targeted booth. Also, it can be used in the bus or train stations to guide the passengers to the desired platform.

Ambient assisted living (AAL) and health applications:

Indoor localization is one of the most important constituent for the AAL tools. AAL tools are advanced tools performing human-machine interactions. AAL tools aim to enhance the health status of the older adults by making them able to control their health conditions. Such applications are used to track and monitor the elderly people. Some of the indoor localization systems based on the AAL applications are “Smart Floor Technology” to detect the presence of people and the “Passive Infrared Sensors” to notice the motion of people. Other applications are based on ultra wide band (UWB) technology. For example, orthopedic computer-aided surgery as well as its integration with smart surgical tools such as wireless probe for real-time bone morphing is implemented[55-57]. UWB positioning system is proven to achieve a real time3D dynamic accuracy of 5.24 mm–6.37 mm. Hence, this dynamic accuracy implies the potential for millimeter accuracy. This accuracy satisfies the requirement of 1 mm–2 mm 3D accuracy for orthopedic surgical navigation systems.

Robotics:

Robotics is one of the main applications of localizations. Many researches and developments are conducted for implementing multi-robot system applications. The movement of robots in large indoor environments, where cooperation between them is required is a critical application of localization. For example, cooperation between robot teams enhances the mission outcomes in applications such as surveillance, unknown zone explorations, guiding or connectivity maintenance [29]. Ubiquitous Networking Robotics in Urban Settings (URUS) project is an excellent example of using localization for evacuation in case of emergency, where the robots lead the people to the evacuation area. Moreover, obstacle avoidance and dynamic and kinematic constraints are considered in robotics to achieve complete navigation system.

Cellular Networks:

Location information can be used to address many challenges in cellular networks. The accuracy of location estimation is gradually improved in several generations of cellular networks. For example, the accuracy is improved from hundreds to tens of meters using cell-ID localization technique in second generation cellular networks. In third generation, the accuracy is improved based on timing via synchronization signal and in fourth generation, a reference signal dedicated for localization purpose is used. As well, localization technologies[9] can be used by numerous devices in the future fifth generation cellular system to attain an accuracy of location estimation in the range of centimeter. Basically, in fifth generation cellular networks, it is expected to use precise localization information through all layers of the communication protocol stack [35]. This is due to the prediction of most of the fifth generation cellular user terminals in their mobility patterns knowing that these terminals will be either associated with fixed or controllable units or people. Last but not least, localization is also required for several jobs in cyber-physical systems, like smart transportation systems [67] and robotics in fifth generation cellular system.

Chapter 5:

Evaluation Criteria for Localization

Evaluating the performance of the localization algorithm is important for researchers, either to validate a new algorithm against the previous state of the art or choosing a localization algorithm that best fit the requirements of the corresponding application scenario. Since different applications will have different needs, it is important for the researcher to decide what performance criteria or evaluation metrics the localization algorithm are to be compared against other algorithms that fits different applications need [42]. A broader set of evaluation criteria are useful both for the developers and the users of the localization algorithms in order to deeply understand the application needs. Examples of the evaluation metrics are localization accuracy, cost, coverage, robustness, scalability, topology etc. These criteria reflect the constraints such as computational complexity and limitations, power consumption, unit cost and network scalability [71]. Some evaluation criteria are binary in nature, such as some algorithms either have some property or they don’t have, e.g., anchor based or anchor free; range based or range free; self configuring or not; etc. Binary criteria can be used by researchers to narrow down the comparative evaluation of an algorithm against others. For example, one can narrow down the comparative evaluation by designing self configuring and range free localization algorithm [45] by immediately limiting the number of comparison against range based solutions.

5.1 . Accuracy

Accuracy is defined as how well the position estimated by the localization algorithm matches the known, ground truth positions. A good localization algorithm should provide the match as closely as possible. However, positional accuracy is not the only over-riding goal of a good localization algorithm [58].This is largely application dependent. Different applications will have different requirements on there solution of the positional accuracy. The granularity of the required positional accuracy depends on the inter-node spacing. If the inter-node spacing is of the order of 100 m, then positional error of 1 m can be tolerable. However, if the inter-node spacing is of the order of 0.5 m, then 1 m error is highly unacceptable. It is also important to measure, how well a localization algorithm achieves good accuracies without a full set of input data [72-75]. For example, some algorithms such as assume measurements from every node to every other node for the localization algorithm to arrive at a stable estimation. This assumption is totally unrealistic given the realities of deployment environments. Evaluation should show how the algorithms performance is affected by measurement noise, bias or uncorrelated error in the input data. It should also determine the number of sensor nodes that can actually be localized [31-34]. Errors in measurement data is important for those algorithms that is designed to work for 2D and assume to work for 3D also. Because in 3D environment, measurement noise can result in flips and reflections of the estimated coordinates of the sensor nodes. The simplest way to calculate accuracy is to determine the residual error between estimated positions and the actual positions for every sensor nodes in the network, sum them and average the result. This is known as mean absolute error[12-15] and is defined as

$$E_{mae} = \frac{\sum_{i=1}^{n} \sqrt{(x_i - \tilde{x_i})^2 + (y_i - \tilde{y_i})^2 + (z_i - \tilde{z_i})^2}}{n}$$

where, (xi, yi, zi) are actual coordinates and (x˜i, y˜i, z˜i) are estimated coordinates of the sensor node. The total number of sensor nodes in the network is n.

The mean average error has the similarity to the root mean square (rms) error [14], which is defined as

$$E_{rms} = max_{i=1 \ldots n} \sqrt{(x_i - \tilde{x_i})^2 + (y_i - \tilde{y_i})^2 + (z_i - \tilde{z_i})^2}$$

It is also important for the accuracy metric to reflect not only the positional error in terms of the distance, but also in terms of the geometry of the network. If only average node position error is used [17],then there is a huge difference in the correctness of the relative geometry of the network estimated by the localization algorithm and the relative geometry of the actual network. This problem was identified by [18] and is addressed by defining the following metric known as global energy ratio.

$$GER = \frac{1}{n(n-1)/2}\sqrt{\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left(\frac{\hat{d}_{ij}-d_{ij}}{d_{ij}}\right)^2}$$

The distance error between the estimated distance (dˆij) and the known distance (dij) is normalized by the known distance (dij), making the error a percentage of the known distance. The GER metric does not reflect the rms error [19] and is addressed by defining an accuracy metric that better reflects the rms error called global distance error (GDE).

GDE =

$$GDE = \frac{1}{R}\sqrt{\frac{\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left(\frac{\hat{d}_{ij}-d_{ij}}{d_{ij}}\right)^2}{n(n-1)/2}}$$

where, R represents the average radio range of a sensor node. The GDE calculates [20] the localization error represented as a percentage of the average distance nodes can communicate over.

5.2 Cost

Cost is defined as how expensive the algorithm is in terms of power consumption, communication overhead, pre-deployment setup (i.e., how many anchor nodes are needed), time taken to localize a sensor node, etc. An algorithm which can minimize several cost[16]constraints is likely to be desirable if maximizing network lifetime is the primary goal. However, cost is an important tradeoff against accuracy and is often motivated by realistic applications requirement. For example, an algorithm may focuses on minimizing communication overhead and complex processing to save power, quick convergence[20] etc., but at the cost of the overall accuracy. Some of the common metrics are described below:

Anchor to Node Ratio:

Minimizing the number of anchors is desirable from the equipment cost or deployment point of view. For example, using too many anchor nodes in the network that estimate their positions by global positioning system must be equipped with a GPS device, which is both power hungry and expensive[23]; thus limiting the overall network lifetime. Similarly, predefined anchor positions are difficult to implement if placement of the nodes (including the anchor nodes) are carried out by a vehicle (e.g., from airplane). The anchor to node ratio is defined as the total number of anchor nodes divided by the total number of nodes in the network. This ratio is very important for the design [22] of a localization algorithm. This metric is useful to calculate the trade-off between localization accuracy, the percentage of the nodes that can be localized against the deployment cost [23]. For example, increasing the number of anchor nodes will lead to high accuracy as well as the percentage of the nodes that can be localized. On the other hand, the deployment cost will increase. A good localization algorithm must investigate the minimum number of anchor nodes that is needed [24,25] for desired accuracy of the application.

Communication Overhead:

Since radio communication is considered to be the most power consuming process relative to the overall power consumption of a wireless sensor node, minimizing communication overhead is a paramount in increasing the overall network lifetime. This metric is evaluated with respect to the scaling of the network[30], i.e., how much do the communication overhead increase as the network increases in size?

Algorithm Complexity:

Algorithmic complexity can be described as the standard notions (big O notation) of computational complexity in time and space. That is how long a localization algorithm runs before estimating the positions of all the nodes in the network and how much memory (storage) is needed [33] for such calculations. For example, as a network increase in size, the localization algorithm with O(n3) complexity is going to take longer time to converge than an algorithm whose complexity is O(n2). The same is true for space complexity.

Convergence Time:

Convergence time is defined as the time taken from gathering localization related data to calculating the position estimates of all the nodes in the network. This metric is evaluated against the network size. That is, how long it takes for a localization algorithm to converge as the network increases [31,32] in size. This metric is also important for some applications with fixed number of nodes in the network. For example, tracking of a moving target requires fast convergence. So, even if any particular localization algorithm that gives very accurate position estimates but takes long time is useless in this scenario [34]. Similarly, if one or more nodes are mobile in a network, the time taken to update positions may not reflect the current physical state of the network if the algorithm is slow.

5.3 Coverage

Coverage is simply a measure of the percentage of the nodes deployed in the network that can be localized, regardless of the localization accuracy. Some localization algorithms may not be able to localize all the nodes in the network. This depends on the density of the nodes as well as the placement of the anchor nodes in the network [55]. In evaluating coverage performance of localization algorithms, one must try various scenarios/strategies of anchor placements as well as various node densities.

One can evaluate how the localization accuracy varies as the number of anchor nodes, placement of anchor nodes or neighbor per nodes varies. There is a saturation point, after which no additional gains in accuracy can be achieved [57]. However, in attempting to minimize the number of anchor nodes or remove them entirely, a localization algorithm may compromise its accuracy and simplicity.

Anchor free localization algorithms are frequently centralized and framed as non-linear optimization problem [110]. These approaches may not be feasible to implement in a resource constraint nodes due to computational complexity.

Density:

If the density of the node deployment is low, it may be impossible to localize many nodes for a localization algorithm with random topology due to the connectivity problem [111].Localization algorithm focusing on denser network should also take care of radio traffic, number of packet collisions, and energy consumption of the nodes as these factors will also increase as the number of nodes increase in the network.

Anchor Placement:

Position of anchor nodes may have a significant impact on the calculation of the localization accuracy. Localization algorithms assumption of uniform grid or predefined placement of anchor nodes gives them high accuracy but failed to reflect the real world situation. Thus, this assumption is unrealistic [17] for any localization algorithms since they do not take into account the environmental factors such as obstacles (that affect the anchor placement), terrain, signal propagation conditions etc. The geometry of the anchor nodes with respect to the unlocalized sensor nodes can have a varying effect on the calculation of the position estimates [9].

5.4. Topologies

Defining real node deployment topologies in simulations can play an important role when comparing the performance of localization algorithms. Different topologies such as uniform grid, C-shape, S-shape, O-shape topologies have significant effect on localization accuracy.

Sensor network topologies can be divided mainly into two categories: even and random. In even topologies, sensor and anchor nodes are placed over the network area in an exact grid. On the other hand, in random topologies, sensor and anchor nodes are placed uniformly and randomly over the network area. Figure 2 shows node deployment in a random topology in an area of 10 m _ 10 m with sensor density 8. Between these two topologies, random topology better reflects the real world deployment scenarios [43]. This is because, in reality, sensor nodes are placed in areas where manual placement is restricted (in forest) or totally impossible (inside volcano). In such cases, sensor nodes are usually scattered in the deployment area from an airplane. So uniform deployment is not guaranteed.

For these reasons, random topologies [52-54] are popular among researchers for evaluating the localization algorithm in simulation and comparison with other state of the arts

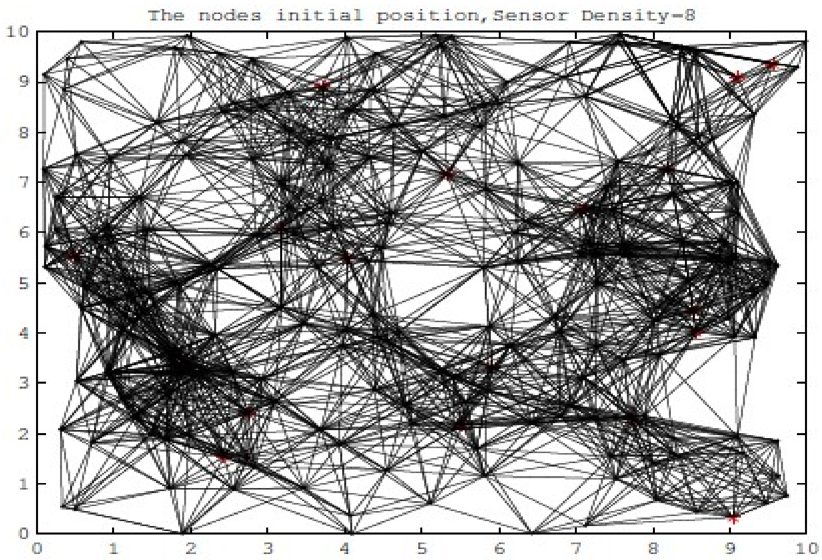


Figure 2. Random uniform topology.

Topologies can be further subdivided into regular and irregular topologies according to the placement strategies of sensor nodes as well as the shape of the obstacles inside the network area.

Regular Topology:

In regular topology, nodes are placed uniformly over an area as a grid or randomly. In such deployment strategy, the average node density becomes consistent over each part of the distributed area. Many well known multi hop localization algorithms [14] estimate the shortest path distance (number of hops multiplied by the average hop distance) between sensor nodes[25] by utilizing this advantage of deployment strategy and derive the actual Euclidean distance from this to estimate the position of the sensor nodes. This gives very accurate position estimates or at least a bounded value. However, this assumption of regular topologies does not reflect the real world condition due to various factors [28] that restrict the deployment of sensor nodes and thus is not effective at all.

Irregular Topology:

In irregular topology, the estimated distance between nodes greatly deviates from the actual Euclidean distance due to the presence of obstacles or other objects inside the network area.

Node density in an individual region may greatly deviate from the average node density of the whole region. Depending on obstacle size and shape inside the network area, the shape of their regular topologies can be C-shaped, S-shaped, L-shaped, O-shaped [67] etc. as can be seen from the Figures 3 and 4 and represent irregular deployment configurations that many applications may find themselves constraint by. Therefore, such topologies are generally useful to compare and stress the various attributes of localization algorithms to prove themselves robust. Note that, in Figures 3 and 4, two nodes can be connected via a detoured path around the obstacles and because of this the difference between the estimated hop distance and the actual Euclidean distance is large[69]. Therefore, individual error in localization algorithms may accumulate, resulting in large localization error in the overall network. Obviously, a localization algorithm that generates accurate results in such topologies are considered to be more robust and useful in many real world applications.

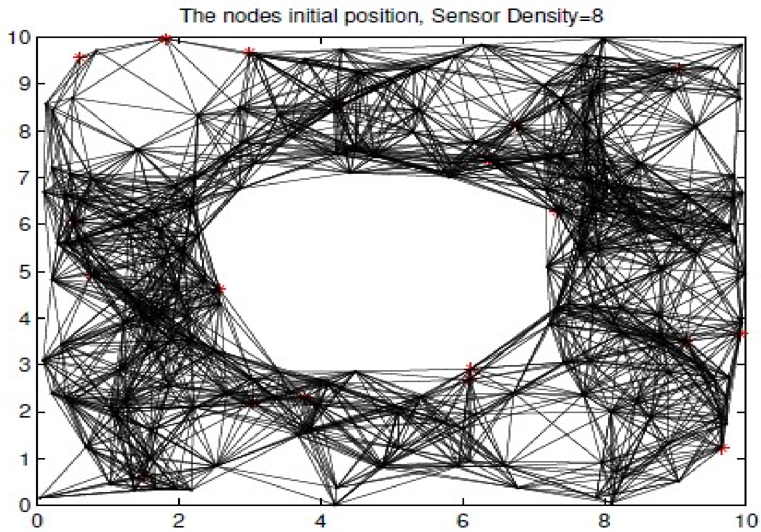


Figure: Irregular Topology: O-shape.

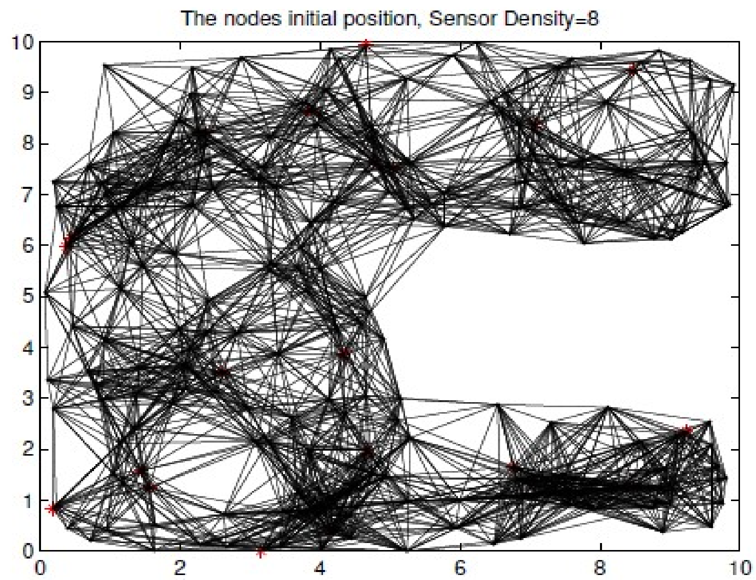
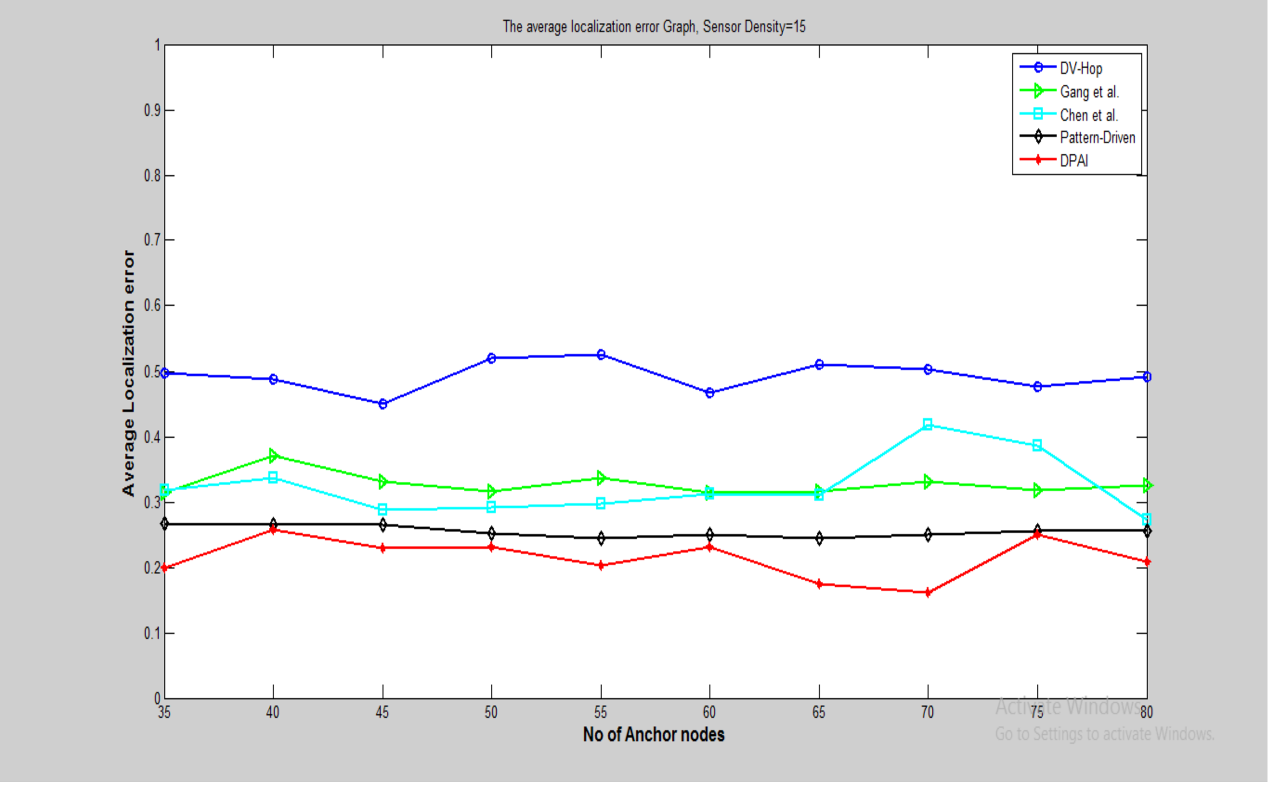
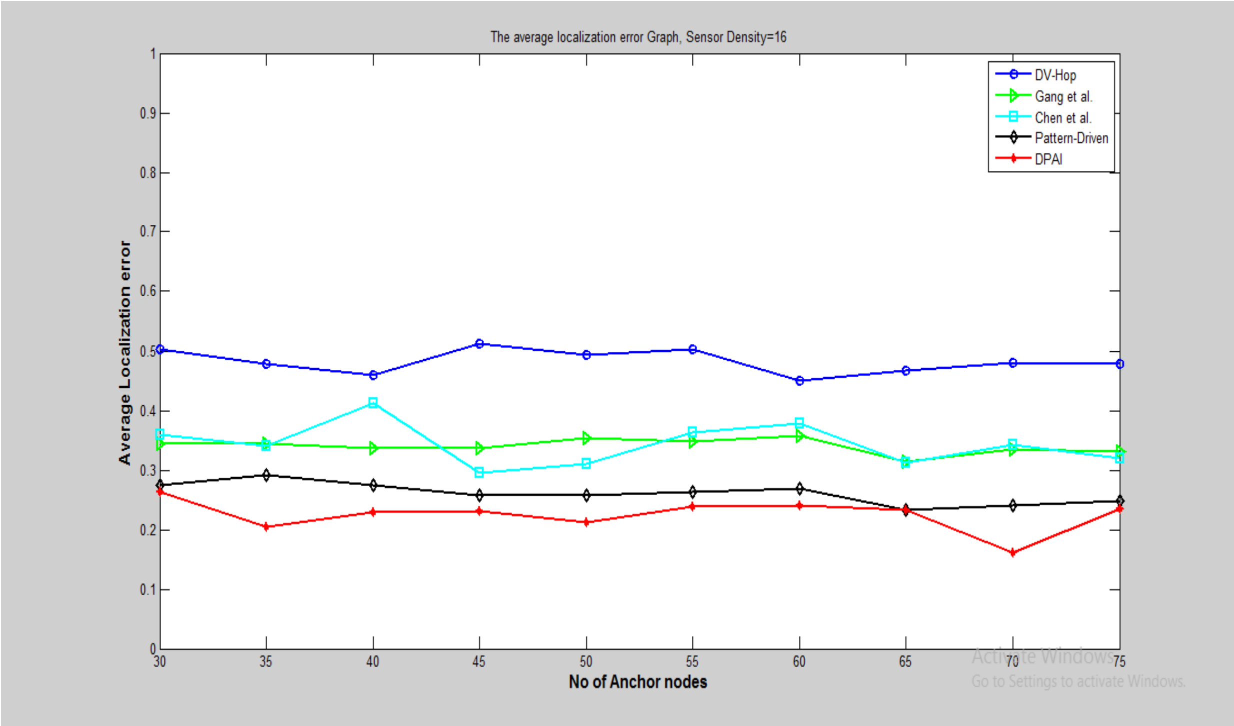


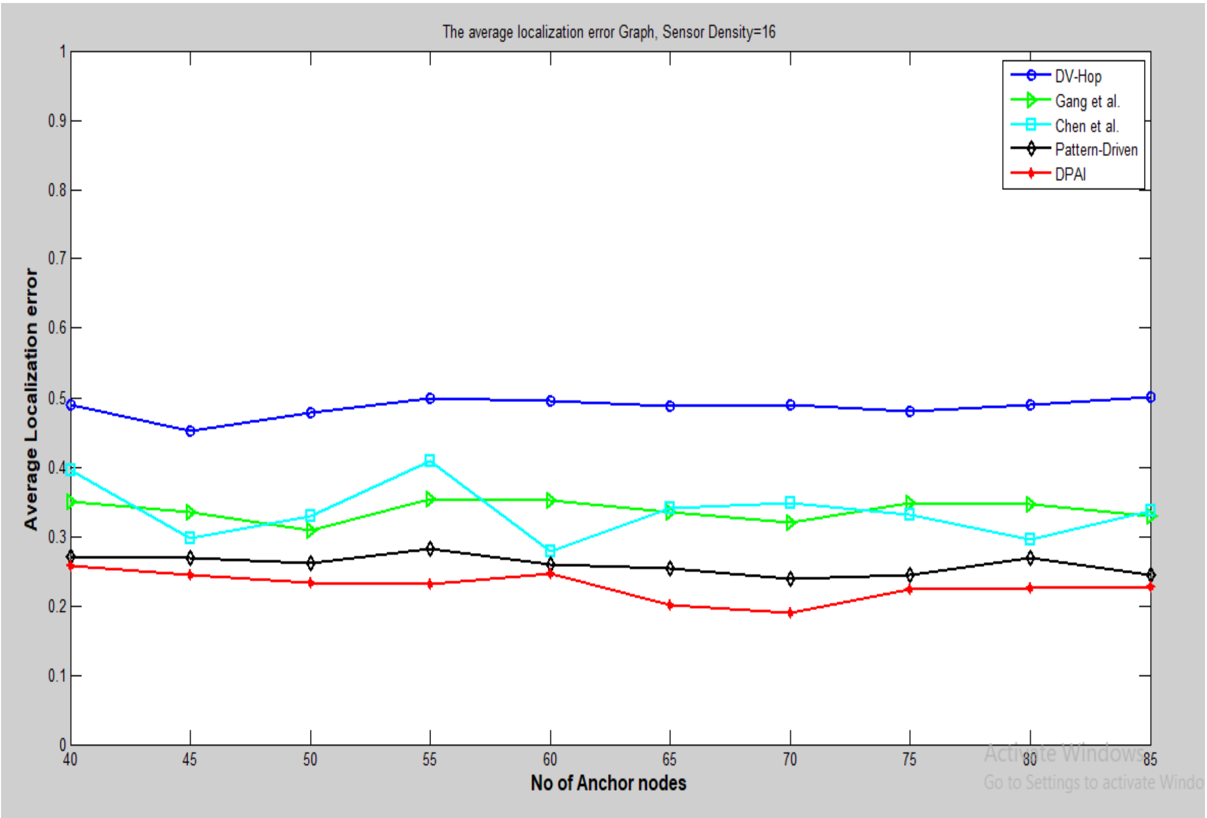
Figure: Irregular Topology: C-shape.

Chapter 6

Result & Discussion







As can be seen from the simulation results of Fig.1 and Fig.2, our improved DV-Hop algorithm achieve better performance than the DV-Hop algorithm. The location error decreases as ratio of anchor nodes increase. For the same ratio of anchor nodes, position error is smaller when our improved DV-Hop scheme applied in same WSNs environment than the DV-Hop algorithm. For example, with 5 anchor nodes (5%), Improved DV-Hop has an average error of about 75%R, where as the DV-Hop has an average error of about 84%R. From Fig.3, we will sure the location coverage improved via using our improved DV-Hop algorithm. For example, with 10 anchor nodes (10%), Improved DV-Hop algorithm reaches location coverage about 100%. The placement of anchor nodes will affect the DV-Hop algorithm. From Fig.2 and Fig. 3, it can be stated that important improvements in the positioning accuracy and location coverage are obtained when uniform anchor placement instead of random anchor placement. Simulation results show that the more regularly anchor nodes are placed, the lower the error. The performance of our Improved DV-Hop scheme exceeds the original DV-Hop location algorithm from our simulation results.

Chapter 7

Future Study & Conclusion

In this section, we summarize different perspectives and challenges in localization that need to be addressed. The challenges may be quite different in different potential applications. The scale of the network in these applications may be small or large and the environment may be different. Traditional localization methods are not suitable for different applications with different environmental challenges. Following are some challenges that need to be solved:

Combining different non-radio frequency techniques:

Use of different non-radio technologies such as visual sensors can compensate for the errors that exist in current localization algorithms. The improved accuracy can be achieved by the additional installation of the costly equipment [101].Therefore, investigating the cost-effective solution will be a promising future direction for research.

Integration of different solution:

Different wireless sensors can be used for the purpose of localization. Different sensor's physical measurement principles are different. Therefore, integrating measurement techniques from different sensors can improve the overall system positioning accuracy.

Scalability:

A scalable localization system means, it performs equally well when its scope gets larger. A localization system may usually require scaling on two dimensions: geographical scaling and sensor density scaling. Geographical scaling means increasing the network area size. On the other hand sensor density scaling means increasing the number of sensors in unit area. Increasing the sensor density posses several challenges [102] in localization. One such challenge is the loss of information due to wireless signal collision. Thus, locating sensors in dense environment should consider such collision while computing position information. A third metric in scaling is system dimension.

Most of the localization algorithm is designed for 2D system. However, recent recommendations (e.g., FCC recommendations) require localization[103] in 3D environment. Because in 3D environment, measurement noise can result in flips and reflections of the estimated coordinates of the sensor nodes.
Thus a localization algorithm works well in 2D may not work perfectly in 3D.

Computational complexity:

Localization algorithms have complexity in terms of software and hardware. Computational complexity means software complexity. That is, how fast a localization algorithm can compute the position information of a sensor node. This is a very critical factor when the computation is done in a distributed way. Because, the energy is spent for computation and for a short battery life sensor, it is highly desirable to have less computational complexity [104,105] localization algorithm.
Additionally, representing various localization algorithms computational complexity analytically is a really difficult task for the researcher to be addressed in future.

Accuracy vs. cost effectiveness:

Different localization system has different positioning accuracy and is dependent on which measurement techniques are used for distance estimation. In range free localization techniques, the accuracy depends on the number of anchor nodes (preinstalled with GPS device) in the network area. Obviously increasing the number of anchor node will increase the accuracy as well as the cost of the overall system [108,109]. Thus, how to achieve high accuracy with minimum number of anchor nodes is an open research problem.

Comparison

The performance of localization algorithm depend on various factors such as accuracy, communication and computation cost, coverage information, computational model, node density, and scalability. The localization schemes can be classified on the basis of certain measures such as: presence of anchor, computational model, presence of GPS, and range measurements. All localization techniques have their own merits and limitations, making them suitable for different applications [106-109]. In this paper, we have performed comprehensive review on various localization techniques and compare them. After that we summarized then comparison in tabular form. The comparison between centralized and distributed localization is summarized in table 1.

However, the summary of comparison between range based and range free schemes is shown in table 2. After that we focused on various range free localization techniques. The comparison of various range free localization schemes is summarized [113-115] in table 3.

Table 1: Summary of comparison between Centralized Techniques and Distributed Techniques

	Centralized Techniques	Distributed Techniques
Cost	More	Less
Power consumption	More	Less
Accuracy	70-75%	75-90%
Dependency on additional hardware	No	Yes
Deploy ability	Hard	Easy

Table 2: Summary of comparison between Range based Techniques and Range free Techniques

	Range based Techniques	Range free Techniques
Cost	More	Less

Power consumption	More	Less
Accuracy	85-95%	70-75%
Dependency on additional hardware	Yes	No
Deploy ability	Hard	Easy

Table 3: Performance summary of popular range free localization techniques

Technique	Node density	Cost	Accuracy	Overhead	Scalability
APIT	>16	Low	Good	Small	Yes
DV-Hop	>8	Medium	Good	Largest	No
Multi-Hop	>12	High	Good	Large	No
Centroid	>0	Low	Fair	Smallest	Yes
Gradient	>6	Low	Average	Large	Yes

Conclusion

Wireless sensor network localization has gain lot of attention of research community. This concern is expected to grow further with the proliferation in sensor network applications. This paper had provided a review of various range free localization techniques and their corresponding localization algorithms for sensor network. In this paper, the taxonomy of localization techniques has been discussed. In this work, we compare the different localization techniques and represent that comparison in tabular form. This paper reported the classification of distributed localization algorithms on the basis of range measurements. Among all studied schemes, this comparative analysis done by us to conclude that each algorithm has its own features and none is absolutely best. On the whole, the range based techniques are either expensive or susceptible to network dynamics. However, the range free techniques are imprecise and easily affected by node density. Regardless of significant research development in this area, some unsolved problems are still there. At the end, we focused on the certain issues need to be addressed. This paper is very useful for the research group those are interested in development, modification and optimization of localization algorithms for wireless sensor networks.

References

1. Vossiek, M.; Wiebking, L.; Gulden, P.; Wieghardt, J.; Hoffmann, C.; Heide, P. Wireless local positioning. IEEE Microw. Mag. **2003**, 4, 77–86.

2. Flora, C.D.; Ficco, M.; Russo, S.; Vecchio, V. Indoor and outdoor location based services for portable wireless devices. In Proceedings of the 25th IEEE International Conference on Distributed Computing Systems Workshops, Columbus, OH, USA, 6–10 June 2005; pp. 244–250.

3. Paul, A.K.; Sato, T. Effective Data Gathering and Energy Efficient Communication Protocol in Wireless Sensor Network. In Proceedings of the Wireless Personal Multimedia Communication (WPMC'11), Brest, France, 3–7 October 2011; pp. 1–5.

4. Al-Karaki, J.N.; Kamal, A.E. Routing techniques in wireless sensor networks: A survey. IEEE Wirel. Commun. **2004**, 11, 6–28.

5. Chowdhury, T.; Elkin, C.; Devabhaktuni, V.; Rawat, D.B.; Oluoch, J. Advances on Localization Techniques for Wireless Sensor Networks. Comput. Netw. **2016**, 110, 284–305.

6. Halder, S.; Ghosal, A. A survey on mobile anchor assisted localization techniques in wireless sensor networks. Wirel. Netw. **2016**, 22, 2317–2336.

7. Paul, A.K.; Sato, T. Detour Path Angular Information Based Range Free Localization in Wireless Sensor Network. J. Sens. Actuator Netw. **2013**, 2, 25–45.

8. Yassin, A.; Nasser, Y.; Awad, M.; Al-Dubai, A.; Liu, R.; Yuen, C.; Raulefs, R.; Aboutanios, E. Recent Advances in Indoor Localization: A Survey on Theoretical Approaches and Applications. IEEE Commun. Surv. Tutor. **2017**, 19, 1327–1346.

9. Paul, A.K.; Li, Y.; Sato, T. A Distributed Range Free Sensor Localization with Friendly Anchor Selection Strategy in Anisotropic Wireless Sensor Network. Trans. Jpn. Soc. Simul. Technol. **2013**, 4, 96–106.

10. Wang, C.; Xiao, L. Sensor Localization in Concave Environments. ACM Trans. Sens. Netw. **2008**, 4, doi:10.1145/1325651.1325654.

11. Piccolo, F.L. A New Cooperative Localization Method for UMTS Cellular Networks. In Proceedings of the IEEE Global Telecommunications Conference (IEEE GLOBECOM), New Orleans, LA, USA, 30 November–4 December 2008; pp. 1–5.

12. Mensing, C.; Sand, S.; Dammann, A. Hybrid data fusion and tracking for positioning with GNSS and 3GPP-LTE. Int. J. Navig. Observ. **2010**, 2010, 1–12.

13. Rezazadeh, J.; Moradi, M.; Ismail, A.S.; Dutkiewicz, E. Superior Path Planning Mechanism for Mobile Beacon-Assisted Localization in Wireless Sensor Networks. IEEE Sens. J. **2014**, 14, 3052–3064.

14. Niculescu, D.; Nath, B. Ad hoc positioning system (APS). In Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM '01), San Antonio, TX, USA, 25–29 November 2001; Volume 5, pp. 2926–2931.

15. Zhong, Z.; He, T. RSD: A Metric for Achieving Range-Free Localization beyond Connectivity. IEEE Trans. Parallel Distrib. Syst. **2011**, 22, 1943–1951.

16. He, T.; Huang, C.; Blum, B.M.; Stankovic, J.A.; Abdelzaher, T. Range-free Localization Schemes for Large Scale Sensor Networks. In Proceedings of the 9th Annual International Conference on Mobile Computing and Networking (MobiCom '03), New York, NY, USA, 14–19 September 2003; pp. 81–95.

17. Boukerche, A.; Oliveira, H.A.B.F.; Nakamura, E.F.; Loureiro, A.A.F. DV-Loc: A scalable localization protocol using Voronoi diagrams for wireless sensor networks. IEEE Wirel. Commun. **2009**, 16, 50–55.

18. Gui, L.; Val, T.; Wei, A. Improving Localization Accuracy Using Selective 3-Anchor DV-Hop Algorithm. In Proceedings of the IEEE Vehicular Technology Conference (VTC Fall), San Francisco, CA, USA, 5–8 September 2011; pp. 1–5.

19. Ta, X.; Mao, G.; Anderson, B.D.O. On the Probability of K-hop Connection in Wireless Sensor Networks. IEEE Commun. Lett. **2007**, 11, 662–664.

20. Ta, X.; Mao, G.; Anderson, B.D.O. Evaluation of the Probability of K-Hop Connection in Homogeneous Wireless Sensor Networks. In Proceedings of the IEEE GLOBECOM 2007—IEEE Global Telecommunications Conference, Washington, DC, USA, 26–30 November 2007; pp. 1279–1284.

21. Kleinrock, L.; Silvester, J. Optimum Transmission Raddi for Packet Radio Networks or Why Six Is a Magic Number. In Proceedings of the IEEE National Telecommunications Conference, Birmingham, AL, USA, 4–6 December 1978; pp. 431–435.
J. Sens. Actuator Netw. **2017**, 6, 24 19 of 23

22. Chen, Y.S.; Lo, T.T.; Ma, W.C. Efficient localization scheme based on coverage overlapping in wireless sensor networks. In Proceedings of the 5th International ICST

Conference on Communications and Networking in China, Beijing, China, 25–27 August 2010; pp. 1–5.

23. Assaf, A.E.; Zaidi, S.; Affes, S.; Kandil, N. Range-free localization algorithm for heterogeneous Wireless Sensor Networks. In Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC), Istanbul, Turkey, 6–9 April 2014; pp. 2805–2810.

24. Vural, S.; Ekici, E. On Multihop Distances in Wireless Sensor Networks with Random Node Locations. IEEE Trans. Mob. Comput. **2010**, 9, 540–552.

25. Kuo, J.C.; Liao,W. Hop Count Distribution of Multihop Paths in Wireless NetworksWith Arbitrary Node Density: Modeling and Its Applications. IEEE Trans. Veh. Technol. **2007**, 56, 2321–2331.

26. Li, M.; Liu, Y. Rendered Path: Range-Free Localization in Anisotropic Sensor Networks With Holes. IEEE/ACM Trans. Netw. **2010**, 18, 320–332.

27. Zhang, S.; Cao, J.; Li-Jun, C.; Chen, D. Accurate and Energy-Efficient Range-Free Localization for Mobile Sensor Networks. IEEE Trans. Mob. Comput. **2010**, 9, 897–910.

28. Xiao, B.; Chen, L.; Xiao, Q.; Li, M. Reliable Anchor-Based Sensor Localization in Irregular Areas. IEEE Trans. Mob. Comput. **2010**, 9, 60–72.

29. Xiao, Q.; Xiao, B.; Cao, J.; Wang, J. Multihop Range-Free Localization in Anisotropic Wireless Sensor Networks: A Pattern-Driven Scheme. IEEE Trans. Mob. Comput. **2010**, 9, 1592–1607.

30. Singh, M.; Bhoi, S.K.; Khilar, P.M. Geometric Constraint Based Range Free Localization Scheme for Wireless Sensor Networks. IEEE Sens. J. **2017**, 17, 5350–5366.

31. Zaidi Assaf, A.E.; Affes, S.; Kandil, N. Range-free node localization in multi-hop wireless sensor networks. In Proceedings of the IEEE Wireless Communications and Networking Conference, Doha, Qatar, 3–6 April 2016; pp. 1–7.

32. Ahmadi, Y.; Neda, N.; Ghazizadeh, R. Range Free Localization in Wireless Sensor Networks for Homogeneous and Non-Homogeneous Environment. IEEE Sens. J. **2016**, 16, 8018–8026.

33. Zaidi, S.; El Assaf, A.; Affes, S.; Kandil, N. Accurate Range-Free Localization in Multi-Hop Wireless Sensor Networks. IEEE Trans. Commun. **2016**, 64, 3886–3900.

34. Han, S.; Lee, S.; Lee, S.; Park, J.; Park, S. Node distribution-based localization for large-scale wireless sensor networks. Wirel. Netw. **2010**, 16, 1389–1406.

35. Patwari, N.; Hero, A., III; Perkins, M.; Correal, N.; O'Dea, R. Relative Location Estimation in Wireless Sensor Networks. Trans. Signal Proc. **2003**, 51, 2137–2148.

36. Bulusu, N.; Heidemann, J.; Estrin, D. GPS-less low-cost outdoor localization for very small devices. IEEE Pers. Commun. **2000**, 7, 28–34.

37. Singh, M.; Khilar, P.M. An Analytical Geometric Range Free Localization Scheme Based on Mobile Beacon Points inWireless Sensor Network. Wirel. Netw. **2016**, 22, 2537–2550.

38. Chen, H.; Shi, Q.; Tan, R.; Poor, H.V.; Sezaki, K. Mobile element assisted cooperative localization for wireless sensor networks with obstacles. IEEE Trans.Wirel. Commun. **2010**, 9, 956–963.

39. Galstyan, A.; Krishnamachari, B.; Lerman, K.; Pattem, S. Distributed Online Localization in Sensor Networks Using a Moving Target. In Proceedings of the 3rd International Symposium on Information Processing in Sensor Networks (IPSN '04), New York, NY, USA, 27–27 April 2004; pp. 61–70.

40. Mei, J.; Chen, D.; Gao, J.; Gao, Y.; Yang, L. Range-Free Monte Carlo Localization for Mobile Wireless Sensor Networks. In Proceedings of the International Conference on Computer Science and Service System, Nanjing, China, 11–13 August 2012; pp. 1066–1069.

41. Hu, L.; Evans, D. Localization for Mobile Sensor Networks. In Proceedings of the 10th Annual International Conference on Mobile Computing and Networking (MobiCom '04), New York, NY, USA, 26 September–1 October 2004; pp. 45–57.

42. He, Z.; Ma, Y.; Tafazolli, R. A hybrid data fusion based cooperative localization approach for cellular networks. In Proceedings of the 7th International Wireless Communications and Mobile Computing Conference, Istanbul, Turkey, 4–8 July 2011; pp. 162–166.

43. Ijaz, F.; Yang, H.K.; Ahmad, A.W.; Lee, C. Indoor positioning: A review of indoor ultrasonic positioning systems. In Proceedings of the 15th International Conference on Advanced Communications Technology (ICACT), PyeongChang, Korea, 27–30 January 2013; pp. 1146–1150. J. Sens. Actuator Netw. **2017**, 6, 24 20 of 23

44. Deak, G.; Curran, K.; Condell, J. Review: A Survey of Active and Passive Indoor Localisation Systems. Comput. Commun. **2012**, 35, 1939–1954.

45. Gu, Y.; Lo, A.; Niemegeers, I. A survey of indoor positioning systems for wireless personal networks. IEEE Commun. Surv. Tutor. **2009**, 11, 13–32.

46. Adalja, D.M. A comparative analysis on indoor positioning techniques and systems. Int. J. Eng. Res. Appl. **2013**, 3, 1790–1796.

47. Al-Ammar, M.A.; Alhadhrami, S.; Al-Salman, A.; Alarifi, A.; Al-Khalifa, H.S.; Alnafessah, A.; Alsaleh, M.Comparative Survey of Indoor Positioning Technologies, Techniques, and Algorithms. In Proceedings of the International Conference on Cyberworlds, Santander, Spain, 6–8 October 2014; pp. 245–252.

48. Vo, Q.D.; De, P. A Survey of Fingerprint-Based Outdoor Localization. IEEE Commun. Surv. Tutor. **2016**, 18, 491–506.

49. Khan, H.; Hayat, M.N.; Rehman, Z.U. Wireless sensor networks free-range base localization schemes: A comprehensive survey. In Proceedings of the International Conference on Communication, Computing and Digital Systems (C-CODE), Islamabad, Pakistan, 8–9 March 2017; pp. 144–147.

50. Mao, G.; Fidan, B. Localization Algorithms and Strategies for Wireless Sensor Networks; Information Science Reference-Imprint of IGI Publishing: Hershey, PA, USA, 2009.

51. Gezici, S.; Tian, Z.; Giannakis, G.B.; Kobayashi, H.; Molisch, A.F.; Poor, H.V.; Sahinoglu, Z. Localization via ultra-wideband radios: A look at positioning aspects for future sensor networks. IEEE Signal Process. Mag. **2005**, 22, 70–84.

52. Niculescu, D.; Nath, B. DV based positioning in ad hoc networks. J. Telecommun. Syst. **2003**, 22, 267–280.

53. Patwari, N.; Ash, J.N.; Kyperountas, S.; Hero, A.O.; Moses, R.L.; Correal, N.S. Locating the nodes: Cooperative localization in wireless sensor networks. IEEE Signal Process. Mag. **2005**, 22, 54–69.

54. Römer, K. The Lighthouse Location System for Smart Dust. In Proceedings of the 1st International Conference on Mobile Systems, Applications and Services (MobiSys '03), New York, NY, USA, 5–8 May 2003; pp. 15–30.

55. Bahl, P.; Padmanabhan, V.N. RADAR: An in-building RF-based user location and tracking system. In Proceedings of the IEEE INFOCOM 2000 Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064), Tel Aviv, Israel, 26–30 March 2000; Volume 2, pp. 775–784.

56. Krishnan, P.; Krishnakumar, A.S.; Ju,W.H.; Mallows, C.; Gamt, S.N. A system for LEASE: Location estimation assisted by stationary emitters for indoor RF wireless networks. In Proceedings of the Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE INFOCOM), Hong Kong, China, 7–11 March 2004; Volume 2, pp. 1001–1011.

57. Prasithsangaree, P.; Krishnamurthy, P.; Chrysanthis, P. On indoor position location with wireless LANs.

In Proceedings of the 13th IEEE International Symposium on Personal, Indoor and Mobile RadioCommunications, PavilhaoAltantico, Lisboa, Portugal, 18 September 2002; Volume 2, pp. 720–724.

58. Ray, S.; Lai, W.; Paschalidis, I.C. Deployment optimization of sensornet-based stochastic location-detectionsystems. In Proceedings of the IEEE 24th Annual Joint Conference of the

IEEE Computer andCommunications Societies, Miami, FL, USA, 13–17 March 2005; Volume 4, pp. 2279–2289.

59. Ji, X.; Zha, H. Sensor positioning in wireless ad-hoc sensor networks using multidimensional scaling.In Proceedings of the Twenty-third AnnualJoint Conference of the IEEE Computer and CommunicationsSocieties IEEE INFOCOM, Hong Kong, China, 7–11 March 2004; Volume 4, pp. 2652–2661.

60. Doherty, L.; Pister, K.S.; Ghaoui, L.E. Convex position estimation in wireless sensor networks. In Proceedingsof the IEEE Conference on Computer Communications, Anchorage, AK, USA, 22–26 April 2001; Volume 3,pp. 1655–1663.

61. Kannan, A.A.; Mao, G.; Vucetic, B. Simulated annealing based localization in wireless sensor network.In Proceedings of the IEEE Conference on Local Computer Networks 30th Anniversary (LCN'05), Sydney,Australia, 17 November 2005.

62. Kannan, A.A.; Mao, G.; Vucetic, B. Simulated Annealing basedWireless Sensor Network Localization withFlip Ambiguity Mitigation. In Proceedings of the IEEE 63rd Vehicular Technology Conference, Melbourne,Victoria, Australia, 7–10 May 2006; Volume 2, pp. 1022–1026.

63. Chen, H.; Sezaki, K.; Deng, P.; So, H.C. An Improved DV-Hop Localization Algorithm forWireless SensorNetworks. In Proceedings of the 3rd IEEE Conference on Industrial Electronics and Applications,Weihai,China, 20–23 August 2008; pp. 1557–1561. J. Sens. Actuator Netw. **2017**, 6, 24 21 of 23

64. Stoleru, R.; He, T.; Stankovic, J.A. Range-Free Localization, Secure Localization and Time Synchronization forWireless Sensor and Ad Hoc Networks; Springer: Berlin, Germany, 2007; Volume 30, pp. 3–31.

65. Singh, M.; Khilar, P.M. Mobile Beacon Based Range Free Localization Method for Wireless Sensor Networks.Wirel. Netw. **2017**, 23, 1285–1300.

66. Savarese, C.; Rabaey, J.; Langendoen, K. Robust Positioning Algorithm for Distributed Ad Hoc WirelessSensor Networks. In Proceedings of the USENIX 2002 Annual Technical Conference, Berkeley, CA, USA,10–15 June 2002 ; pp. 317–327.

67. Gang, P.; Yuanda, C.; Limin, C. Study of Localization Schemes for Wireless Sensor Networks. J. Comput.Eng. Appl. **2004**, 40, 27–29.

68. Chen, H.; Sezaki, K.; Deng, P.; So, H.C. An Improved DV-Hop Localization Algorithm with Reduced NodeLocation Error for Wireless Sensor Networks. IEICE Trans. Fundam. **2008**, 91, 2232–2236.

69. Liu, M.; Bao, Y.; Liu, H. An Improvement of DV-Hop Algorithm in Wireless Sensor Networks.J. Microcomput. Inf. **2009**, 25, 128–129.

70. Liu, K.; Yan, X.; Hu, F. A modified DV-Hop localization algorithm for wireless sensor networks.
In Proceedings of the IEEE International Conference on Intelligent Computing and Intelligent Systems,
Shanghai, China, 20–22 November 2009; Vulume 3, pp. 511–514.

71. Langendoen, K.; Reijers, N. Distributed Localization in Wireless Sensor Networks: A QuantitativeComparison. Comput. Netw. **2003**, 43, 499–518.

72. Shang, Y.; Shi, H.; Ahmed, A. Performance Study of Localization Methods for Ad Hoc Sensor Networks.

In Proceedings of the IEEE International Conference on Mobile Ad-hoc and Sensor Systems, Fort Lauderdale,FL, USA, 25–27 October 2004; pp. 184–193.

73. Ssu, K.F.; Ou, C.H.; Jiau, H.C. Localization with mobile anchor points in wireless sensor networks.
IEEE Trans. Veh. Technol. **2005**, 54, 1187–1197.

74. Lee, S.; Kim, E.; Kim, C.; Kim, K. Localization with a mobile beacon based on geometric constraints inwireless sensor networks. IEEE Trans. Wirel. Commun. **2009**, 8, 5801–5805.

75. Xiao, B.; Chen, H.; Zhou, S. Distributed Localization Using a Moving Beacon in Wireless Sensor Networks.IEEE Trans. Parallel Distrib. Syst. **2008**, 19, 587–600.

76. Dong, L.; Severance, F.L. Position estimation with moving beacons in wireless sensor networks.In Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC), Kowloon,
China, 11–15 March 2007; pp. 2319–2323.

77. Pedersen, C.; Pedersen, T.; Fleury, B.H. A variational message passing algorithm for sensor self-localization inwireless networks. In Proceedings of the IEEE International Symposium on Information Theory Proceedings,
St. Petersburg, Russia, 31 July–5 August 2011; pp. 2158–2162.

78. Savic, V.; Wymeersch, H.; Penna, F.; Zazo, S. Optimized edge appearance probability for cooperativelocalization based on tree-reweighted nonparametric belief propagation. In Proceedings of the IEEEInternational Conference on Acoustics, Speech and Signal Processing (ICASSP), Prague, Czech Republic,22–27 May 2011; pp. 3028–3031.

79. Noureddine, H.; Gresset, N.; Castelain, D.; Pyndiah, R. A new variant of Nonparametric Belief Propagationfor self-localization. In Proceedings of the 17th International Conference on Telecommunications, Doha,Qatar, 4–7 April 2010; pp. 822–827.

80. Hadzic, S.; Bastos, J.; Rodriguez, J. Reference node selection for cooperative positioning using coalitionformation games. In Proceedings of the 9th Workshop on Positioning, Navigation and Communication,Dresden, Germany, 15–16 March 2012; pp. 105–108.

81. Zirari, S.; Denis, B. Comparison of links selection criteria for mobile terminal positioning incooperative heterogeneous networks. In Proceedings of the 20th International Conference on Software,Telecommunications and Computer Networks, Split, Croatia, 11–13 September 2012; pp. 1–6.

82. Kemppi, P.; Rautiainen, T.; Ranki, V.; Belloni, F.; Pajunen, J. Hybrid positioning system combiningangle-based localization, pedestrian dead reckoning and map filtering. In Proceedings of the InternationalConference on Indoor Positioning and Indoor Navigation, Zurich, Switzerland, 15–17 September2010; pp. 1–7.

83. Tarrío, P.; Besada, J.A.; Casar, J.R. Fusion of RSS and inertial measurements for calibration-free indoorpedestrian tracking. In Proceedings of the 16th International Conference on Information Fusion, Istanbul,
Turkey, 9–12 July 2013; pp. 1458–1464.J. Sens. Actuator Netw. **2017**, 6, 24 22 of 23

84. Wang, H.; Lenz, H.; Szabo, A.; Bamberger, J.; Hanebeck, U.D. WLAN-Based Pedestrian Tracking UsingParticle Filters and Low-Cost MEMS Sensors. In Proceedings of the 4thWorkshop on Positioning, Navigationand Communication, Hannover, Germany, 22 March 2007; pp. 1–7.

85. Woodman, O.; Harle, R. Pedestrian Localisation for Indoor Environments. In Proceedings of theInternational Conference on Ubiquitous Computing (UbiComp ’08), New York, NY, USA, 21–24 September2008; pp. 114–123.

86. Hattori, K.; Kimura, R.; Nakajima, N.; Fujii, T.; Kado, Y.; Zhang, B.; Hazugawa, T.; Takadama, K. Hybrid. Indoor Location Estimation System Using Image Processing and WiFi Strength. In Proceedings of theInternational Conference on Wireless Networks and Information Systems, Shanghai, China, 28–29 December2009; pp. 406–411.

87. Germa, T.; Lerasle, F.; Ouadah, N.; Cadenat, V.; Devy, M. Vision and RFID-based person tracking in crowdsfrom a mobile robot. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots andSystems, St. Louis, MO, USA, 10–15 October 2009; pp. 5591–5596.

88. Schulz, D.; Fox, D.; Hightower, J. People Tracking with Anonymous and ID-sensors Using Rao-BlackwellisedParticle Filters. In Proceedings of the 18th International Joint Conference on Artificial Intelligence(IJCAI’03), Acapulco, Mexico, 9–15 August 2003; Morgan Kaufmann Publishers Inc.: San Francisco, CA,USA; pp. 921–926.

89. Pescaru, D.; Curiac, D. Anchor Node Localization for Wireless Sensor Networks Using Video and CompassInformation Fusion. Sensors **2014**, 14, 4211–4224.

90. Gao, D.; Zhu,W.; Xu, X.; Chao, H. A hybrid localization and tracking system in camera sensor networks.Int. J. Commun. Syst. **2014**, 27, 606–622.

91. Khan, M.I.; Syrjarinne, J. Investigating effective methods for integration of building's map with low costinertial sensors and wifi-based positioning. In Proceedings of the International Conference on IndoorPositioning and Indoor Navigation, Montbeliard-Belfort, France, 28–31 October 2013; pp. 1–8.

92. Chen, J.C.; Yao, K.; Hudson, R.E. Source localization and beamforming. IEEE Signal Process. Mag.**2002**, 19, 30–39.

93. Rabbat, M.; Nowak, R. Distributed optimization in sensor networks. In Proceedings of the Third InternationalSymposium on Information Processing in Sensor Networks, Berkeley, CA, USA, 26–27 April 2004; pp. 20–27.

94. Capkun, S.; Hamdi, M.; Hubaux, J.P. GPS-free positioning in mobile ad-hoc networks. In Proceedingsof the 34th Annual Hawaii International Conference on System Sciences, Maui, Hawaii, 3–6 January2001; pp. 3481–3490.

95. Kwon, O.H.; Song, H.J. Localization through Map Stitching in Wireless Sensor Networks. IEEE Trans.Parallel Distrib. Syst. **2008**, 19, 93–105.

96. Qudah, I.; Leijdekkers, P.; Gay, V. Using mobile phones to improve medication compliance and awarenessfor cardiac patients. In Proceedings of the 13rd International Conference on PErvasive Technologies Relatedto Assistive Environments, Samos, Greece, 23–25 June 2010; pp. 1–7.

97. Ye, H.; Gu, T.; Tao, X.; Lu, J. F-Loc: Floor localization via crowdsourcing. In Proceedings of the 20th IEEEInternational Conference on Parallel and Distributed Systems (ICPADS), Hsinchu, Taiwan, 16–19 December2014; pp. 47–54.

98. Mahfouz, M.R.; Zhang, C.; Merkl, B.C.; Kuhn, M.J.; Fathy, A.E. Investigation of High-Accuracy Indoor 3-DPositioning Using UWB Technology. IEEE Trans. Microw. Theory Tech. **2008**, 56, 1316–1330.

99. URUS: Ubiquitous Networking Robots in Urban Settings. Available online: http://www.iri.upc.edu/files/scidoc/949-URUS:-Ubiquitous-Networking-Robotics-for-Urban-Settings.pdf (accessed on 10 August 2017).

100. Fazenda, P.V.; Lima, P.U. Non-holonomic robot formations with obstacle compliant geometry. IFAC Proc. Vol.**2007**, 40, 439–444.

101. Taranto, R.D.; Muppirisetty, S.; Raulefs, R.; Slock, D.; Svensson, T.; Wymeersch, H. Location-AwareCommunications for 5G Networks: How location information can improve scalability, latency, and robustnessof 5G. IEEE Signal Process. Mag. **2014**, 31, 102–112.

102. Slock, D. Location aided wireless communications. In Proceedings of the 5th International Symposium on
Communications, Control and Signal Processing, Rome, Italy, 2–4 May 2012; pp. 1–6.

103. Dammann, A.; Agapiou, G.; Bastos, J.; Brunelk, L.; Garcia, M.; Guillet, J.; Ma, Y.; Ma, J.; Nielsen, J.J.;
Ping, L.; et al. WHERE2 Location Aided Communications. In Proceedings of the 19th EuropeanWirelessConference, Guildford, UK, 16–18 April 2013; pp. 1–8.
J. Sens. Actuator Netw. **2017**, 6, 24 23 of 23

104. Daniels, R.C.; Heath, R.W. Link Adaptation with Position/Motion Information in Vehicle-to-VehicleNetworks. IEEE Trans. Wirel. Commun. **2012**, 11, 505–509.

105. Shang, Y.; Ruml, W.; Zhang, Y.; Fromherz, M.P.J. Localization from Mere Connectivity. In Proceedings of the4th ACM International Symposium on Mobile Ad Hoc Networking & Computing (MobiHoc '03), Annapolis,MD, USA, 1–3 June 2003; ACM: New York, NY, USA; pp. 201–212.

106. Allen, M.; Gaura, E.; Newman, R.; Mount, S. Experimental Localization with MICA2 Motes. In Proceedingsof the Technical Proceedings of the 2006 NSTI Nanotechnology Conference and Trade Show, Boston, MA,USA, 1–11 May 2006; pp. 435–440.

107. Broxton, M.; Lifton, J.; Paradiso, J.A. Localization on the Pushpin Computing Sensor Network Using SpectralGraph Drawing and Mesh Relaxation. SIGMOBILE Mob. Comput. Commun. Rev. **2006**, 10, 1–12.

109. Ahmed, A.A.; Shi, H.; Shang, Y. SHARP: A new approach to relative localization in wireless sensornetworks. In Proceedings of the IEEE International Conference on Distributed Computing SystemsWorkshops, Columbus, OH, USA, 6–10 June 2005; pp. 892–898.

110. Girod, L.; Lukac, M.; Trifa, V.; Estrin, D. The Design and Implementation of a Self-calibrating DistributedAcoustic Sensing Platform. In Proceedings of the 4th International Conference on Embedded NetworkedSensor Systems (SenSys ’06), Boulder, CO, USA, 31 October–3 November 2006; ACM: New York,NY, USA; pp. 71–84.

111. Basaran, C.; Baydere, S.; Kucuk, G. RH+: A Hybrid Localization Algorithm forWireless Sensor Networks.IEICE Trans. Commun. **2008**, E91.B, 1852–1861.