Localization
in
Wireless Sensor Networks

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Certificate

This is to certify that the work in the thesis entitled ***"Localization in Wireless Sensor Networks"*** by ***Haroon Rashid*** is a record of an original research work carried out under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology (Research) in Computer Science and Engineering, National Institute of Technology, Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Dr. Ashok Kumar Turuk
Associate Professor
CSE department of NIT Rourkela

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Abstract

The technique of finding physical co-ordinates of a node is known as localization. Importance of localization arises from the need to tag the sensed data and associate events with their location of occurrence. Location information of a sensor node can be obtained by using GPS. But, installing GPS in every node is not a feasible solution. This is because: *(i)* sensor nodes are deployed in a very large number. Installing GPS at every node will increase the cost as well as size, *(ii)* GPS consume power, which will effect the network lifetime. Moreover, location cannot be pre-programmed as it is un-known where nodes will be deployed during their operational phase.

In this thesis, we have made an attempt to address localization in static as well as mobile sensor networks. For static network we have proposed two distributed range based localization techniques called (i) Localization using a single anchor node (LUSA), (ii) Distributed binary node localization estimation (DBNLE). Both the techniques are proposed for grid environment. In LUSA, we have identified three types of node: anchor, special and unknown node. For every anchor node there exists two special node and they are placed perpendicular to the anchor node. Localization in LUSA is achieved by a single anchor node and two special nodes. Localization occurs in two steps. First special nodes are localized and then the unknown nodes. We have compared LUSA with a closely related localization technique called Multi-duolateration (MDL). It is observed that the localization error and localization time is lesser in LUSA. In DBNLE a node is localized with only two location aware nodes instead of three nodes in most localization techniques. This not only reduces the localization time but also the dependency.

For mobile WSNs, we have proposed a distributed localization technique called dead reckoning localization in mobile sensor networks (DRLMSN). In DRLMSN, localization is done at discrete time intervals called *checkpoint*. Unknown nodes are localized for the first time using three anchor nodes. In their subsequent localization, only two anchor nodes are used. Using Bézouts theorem, we estimate two possible locations of a node. A dead reckoning approach is used to select one among the two estimated locations. We have used Castalia simulator to evaluate the performance of the schemes.

Dissemination of Work

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2. **H. Rashid**, A. K. Turuk, "Dead Reckoning Localization Technique for Mobile Wireless Sensor Networks", *IET Wireless Sensor Systems*, 2013. [**Accepted With Revision**]

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Chapter 1

Introduction

Wireless Sensor Networks (WSNs) has become an emerging area of interest among the academia and industry in the last one decade [1]. It consists of a large number of densely deployed nodes which are tiny, low power, in-expensive, multi-functional and have limited computational and communication capabilities. These nodes interact with their environment, sense the parameters of the interest such as temperature, light, sound, humidity, and pressure; and report it to the sink node/base station. Deployment of WSN may vary from a controlled indoor environment to a remote and inaccessible area. Therefore, a sensor node is configured with necessary extra components for on-board limited processing ability, communication, and storage capabilities. A typical WSN is shown in Figure - 1.1.

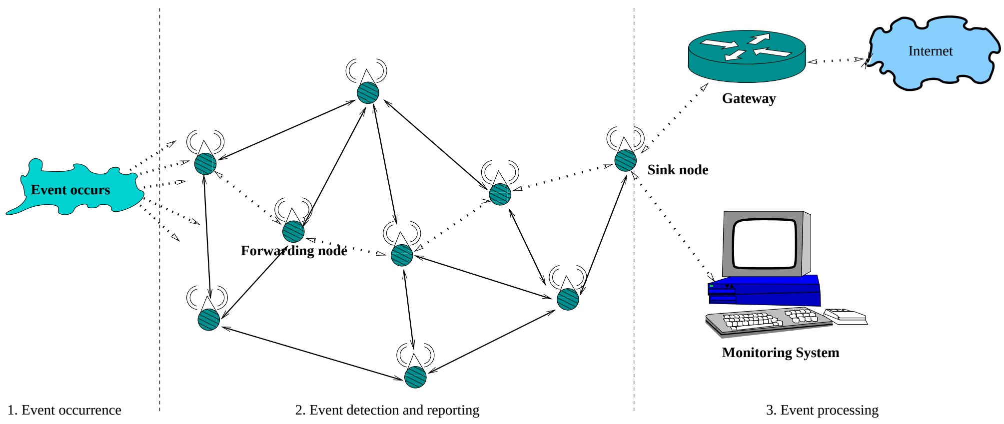


Figure 1.1: Wireless Sensor Network.

With the span of time, usage of WSN in diverse field have increased with the agile growth in micro-electromechanical systems (MEMS), very large scale integration (VLSI), low-power radios, and wireless communication protocols. Applications of WSN includes environment monitoring (e.g., habitat, geophysical monitoring) [2–4], traffic management [5], military applications (e.g., surveillance and battle field monitoring) [6], health monitoring (e.g., medical sensing) [7, 8], industrial process control, context-aware computing (e.g., smart homes, remote metering), infrastructure protection (e.g., bridges, tunnels) [9] and so on.

For interoperability, sensor nodes produced by different manufacturer need to follow a particular standard. Protocol stack of WSN consists of five layers: (*i*) physical layer, (*ii*) data-link layer, (*iii*) network layer, (*iv*) transport layer, and (*v*) application layer [10]. Physical and data-link layer operations are specified by the task group 4 of IEEE 802.15, accordingly named as IEEE 802.15.4. The remaining layers of WSN follow the *ZigBee* standard, developed by the ZigBee Alliance, which consists of various companies working for low-power, reliable and open global wireless networking standards focused on control, monitoring, and sensor applications. An overview of protocol stack in WSNs and the main functions performed at each layer is shown in Figure - 1.2.

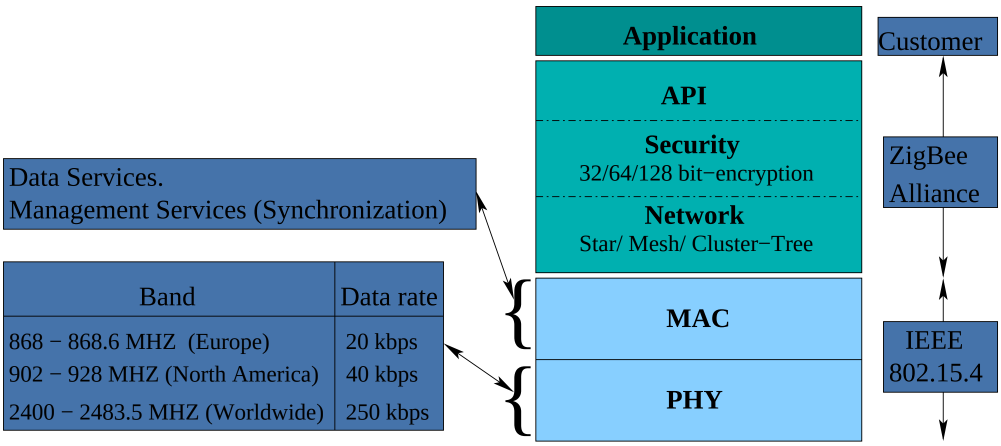


Figure 1.2: Protocol stack of wireless sensor network.

1.1 Key Issues in Wireless Sensor Networks

Some of the important issues in WSNs are stated below:

(*i*) **Energy Efficiency:** Sensor nodes have limited battery capacity. This puts a constraint for other applications and on the lifetime of sensor node. Major sources of battery drainage include: (*i*) continuous sensing, (*ii*) transmission and reception modes of radio. Therefore, to increase the lifetime in unattended environments, efficient algorithms should be developed at each layer of WSN in concern with the less energy utilization. This includes techniques of data compression, data fusion (removal of data redundancy), rotation of cluster heads, and adaptive mechanisms for radio operations.

(*ii*) **Routing:** Topology of WSN changes too frequently; as new nodes are added or some nodes die due to meager resources. Therefore, to increase the connectivity, coverage, and remain updated of network topology, neighbour information should be disseminated timely. Furthermore, transmitting node should identify the best reliable shortest path to the sink node/base station. Therefore, routing serves as a bottleneck in overall efficiency of WSN.

(*iii*) **Time Synchronization:** Synchronizing time in sensor nodes serves as a basic pre-requisite for various applications and protocols such as Time division multiple access (TDMA), Time difference of arrival (TDoA), Time of arrival (ToA) and so on. Basic property of WSNs, *i.e.*, co-operation in communication, computation, sensing and actuation of different nodes solely depends on the time synchronization among nodes [11].

(*iv*) **Fault-Tolerance:** Reliability in WSNs is oftenly affected by various faults arising from environmental hazards, battery depletion, hardware malfunctioning and so on. Individual node failures should not affect the global performance of WSNs. This rate of failure may be high in harsh or hostile environments. In such cases, intended purpose of WSN is achieved by techniques such as load balancing, etc. Nodes should have the capability of self-testing, self-calibrating, self-recovering and so on [12].

(*v*) **Localization:** For robust WSN, localization of nodes is one of the most important issue. Information sensed by a sensor node becomes useful only when its geographical location is tagged. Geographical routing is possible only after the localization, and other issues like spatial querying and load balancing can also be achieved [13].

(*vi*) **Security:** This is one of the critical issues in WSN deployments - where the purpose is to get battle-field awareness or vigilance in confidential data monitoring systems. In such cases, a node can be compromised at any layer if the security is not properly implemented say:

  (*a*) At application layer - to send the bogus data,

  (*b*) At network layer - to change the routing information,

  (*c*) At data-link layer - to schedule data transfer at inappropriate time slots resulting in network jam.

In such cases, WSN should enable: (*i*) intrusion detection to prevent the integrity of collected information, (*ii*) authentication system - to keep information privacy.

For smooth functioning of WSNs each issue needs deep investigation. Some of these issues like synchronization, localization and data gathering needs much more attention. This is because these not only help in attaining the basic function of WSNs but also serve as prerequisite for other applications. In this thesis, we have concentrated on the localization issues in WSNs.

1.2 Motivation

Data gathered by a sensor node is usually reported to the sink for necessary action. For initiating a prompt action the sink must be aware of the location information of the reporting node. For example, assume that fire has occurred in some part of the forest and a nearby sensor report this information to the sink. For quick response, the reporting sensor should include its location along with other information. Tagging of location stamp along with the sensed information is possible only when the reporting node is localized. This signifies the importance of localizing a node prior to its data collection process. A few applications indicating the importance of localization in WSNs is listed below:

(*i*) Sensors gather vital security related parameters such as radio communication, vigorous movements in an surveillance area, and report these to the back-end security system (a sink node). A prompt action by security personnel is possible only if location information is provided with the sensed information [14].

(*ii*) On some occasions, some nodes may die due to the battery drainage or by physical forces. In such cases, new nodes to be injected or battery replacements can be achieved efficiently by adopting geographic routing rather than physical routing schemes [14]. Geographic routing eases task of locating a faulty node as compared to physical routing.

(*iii*) Location information is also used to divide the WSN into different clusters to facilitate collaborative processing and hierarchical routing. For each cluster, one node is chosen as cluster head which remains responsible for cluster interconnectivity and state maintenance.

(*iv*) Sensor networks is like a distributed database for users to query the physical world for useful information. With localization, efficient spatial querying by a sink or a gateway node is responded only by the intended sensor node.

(*v*) Location based routing saves significant energy by eliminating the need for route discovery and improve caching behaviour for applications where requests are location dependent [15].

(*vi*) Determining the quality of coverage of all active sensors using their position.

1.3 Objective

Sensor nodes are low cost devices. Use of GPS to obtain location information will increase their cost. An alternative to the use of GPS is to obtain location information through localization algorithms. Use of localization algorithms mandate the deployment of a few location aware node. The remaining nodes are localized with the help of these location aware nodes. The objective of this thesis includes:

(*i*) Localization using lesser number of location-aware nodes.

(*ii*) Develop a localization algorithm with no extra hardware cost.

(*iii*) Reduce the localization error, and localization time.

1.4 Organization of The Thesis

The thesis is organized into following chapters:

Chapter 1: A brief introduction to wireless sensor networks is provided. Some of the key issues in WSNs are identified. The importance of localization in WSNs is discussed.

Chapter 2: This chapter introduces the localization system. A brief review of different localization schemes is presented.

Chapter 3: This chapter proposes a localization technique for grid environment. A single anchor node is used for localization. The proposed technique is compared with a contemporary proposed for grid environment called multi-duolateration (MDL). We observed that the proposed scheme has lesser localization time and error.

Chapter 4: In this chapter, we proposed a range based, distributed localization algorithm for grid environment. We call the proposed scheme a Distributed Binary Node Localization

Estimation (DBNLE). It uses two reference/localized nodes for localization.

Chapter 5: This chapter proposes a localization technique called Dead Reckoning Localization (DRLMSN) for mobile WSN. In this technique both the unknown and anchor nodes are mobile. Through simulation, we have studied the impact of node mobility, anchor density, node density and deployment topology on location estimation.

Chapter 6: A few conclusions, along with the future scope for research in localization of WSNs is mentioned in this chapter.

Chapter 2

Localization System

The objective of localization is to find the physical coordinates of sensor nodes. These coordinates can be either global or relative. Localization is achieved with the help of a few *location aware* nodes usually referred as *seeds/anchor nodes/beacon nodes.* These anchor nodes are either manually programmed with their physical position or use the global positioning system (GPS) to determine their location.

There are three different stages in localization as shown in Figure - 2.1. They are: (*i*) distance/angle estimation between the nodes, (*ii*) position calculation of a single node, (*iii*) a localization algorithm - used for localization of whole network. Different techniques with varying accuracy and complexity exist at each stage. Localization error and localization time is the cumulative error and time respectively of each stage. These stages are explained in detail in subsequent sections.

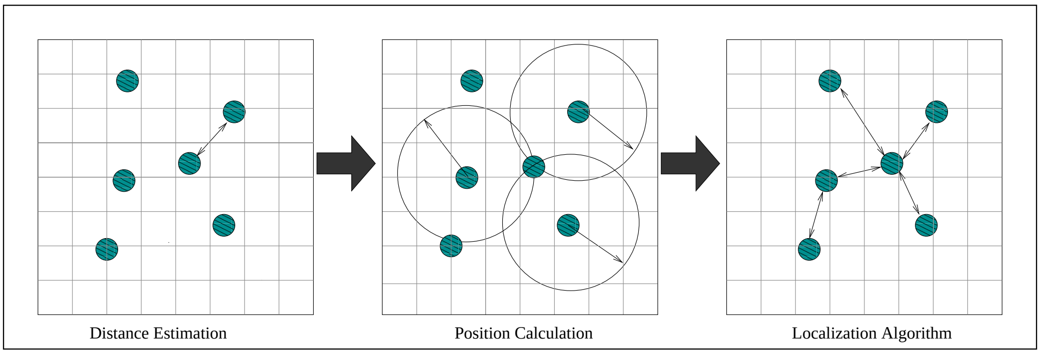


Figure 2.1: Three components of localization system.

2.1 Distance/Angle Estimation

This refers to the measurement of distance or angle between the transmitter and receiver node. Distance/Angle estimation is the pre-requisite for remaining two phases of localization. Different techniques for distance/angle estimation include: time of arrival (ToA), time difference of arrival (TDoA), received signal strength indicator (RSSI), and angle of arrival (AoA).

2.1.1 Time of Arrival

This technique estimates the distance by calculating the time required by a signal to traverse from transmitter to receiver. Types of signal used includes: RF, acoustic, infrared and ultrasound. GPS enabled devices use this technique for distance estimation.

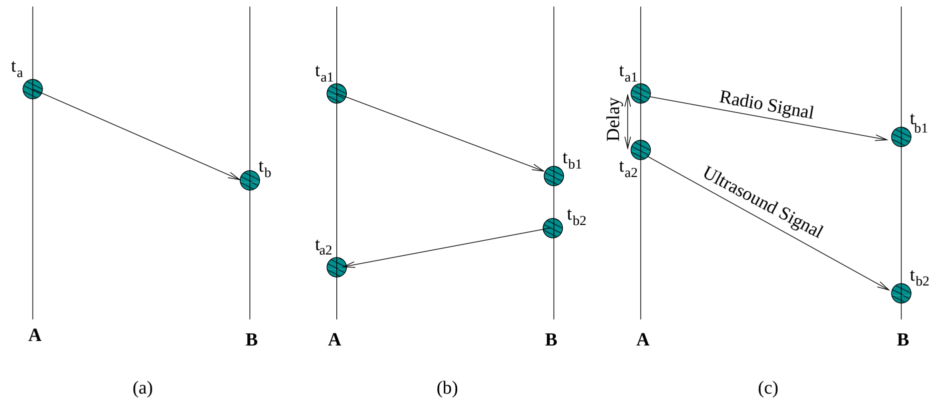


Figure 2.2: (a) ToA, (b) ToA using RTT, (c) TDoA

We consider Figure - 2.2(a) to illustrate distance estimation using ToA. Let node A be the sender and B the receiver, t_a is the time at which a signal is transmitted from A and t_b be the time at which it is received at B, and v be the velocity of signal. Distance d between A and B is estimated as:

$$d = (t_b - t_a) \times v$$

Since, nodes are mostly not synchronized, distance between nodes at various instances as calculated above may vary. Also, the signal (mostly ultrasound signals) speed may vary. This is because they are oftenly affected by temperature, humidity and pressure. Therefore, to remove the problem of synchronization ToA is reformed with round trip time (RTT). This is shown in Figure - 2.2(b). Node A transmit a signal at t_{a1} and node B receive at t_{b1}. After some processing B retransmit a signal to A at t_{b2}, and A receive it at t_{a2}. Distance d is calculated as:

$$d = \frac{((t_{a2} - t_{a1}) - (t_{b2} - t_{b1})) \times v}{2}$$

Further, it is assumed the path traversed by signal is symmetrical.

ToA provides a good level of accuracy, but requires relatively fast processing sensor nodes in order to resolve timing differences for accurate distance measurement. Further, the accuracy of ToA depends upon the receiver ability to accurately estimate the arrival time of received signal. This is oftenly affected by the multipath signal and shadowing.

2.1.2 Time-Difference of Arrival

Time-Difference of Arrival (TDoA) uses the same approach as ToA. But it use two different signals say RF and ultrasound signal of different velocity. This removes the need of synchronization between the nodes. In TDoA, each node is equipped with a speaker and a microphone. Various localization systems such as Cricket [16], Active Bat [17], and Cricket Compass [18] uses TDoA for distance estimation.

Distance estimation using TDoA is shown in Figure - 2.2(c). Node A transmits a radio signal with velocity v_1 at t_{a1} and node B received the signal at t_{b1}. Distance d calculated as

$$d = (t_{b1} - t_{a1}) \times v_1 \tag{2.1}$$

After some delay (possibly 0) node A transmit an ultrasound signal with velocity v_2 at t_{a2} and node B received the signal at t_{b2}. Distance d calculated as

$$d = (t_{b2} - t_{a2}) \times v_2 \tag{2.2}$$

Solving equation 2.1 and 2.2 we get d as

$$d = (t_{b2} - t_{a2}) - (t_{b1} - t_{a1})) \times [\frac{v_1 \times v_2}{v_1 - v_2}] \tag{2.3}$$

TDoA works efficiently under line-of-sight conditions. But achieving line-of-sight condition is difficult to met in some environments. Extra hardware such as speakers, microphones, etc. removes the need of synchronization. Speakers and microphones used should be properly calibrated, and the signals should not be effected by external factors as in ToA.

2.1.3 Received Signal Strength Indication

Radio signal attenuates as the distance between the transmitter and receiver increases. With the increase in distance, strength of radio signal decreases exponentially. The attenuation in signal strength is measured by the receivers received signal strength indicator (RSSI) circuit. RSSI estimates the distance covered by a signal to the receiver by measuring the power of received signal. Decrease in transmitted power at the receiver can be calculated and translated into an estimated distance. An ideal radio propagation model predicts the distance d as:

$$P_r(d) = \frac{P_\lambda G_t G_r \lambda^2}{4\pi^2 d^n L} \tag{2.4}$$

where P_λ is the transmitted power, G_t and G_r is the antenna gain of the transmitter and receiver respectively, L is the system loss, and λ is the system wavelength. Usually G_t, G_r, and L are set to 1. The usage of RSSI in distance calculation can be interpreted as [19]:

$$P_r(d) = P_r(d_0) + 10 \cdot \eta \cdot log(\frac{d}{d_0}) + X_\sigma \tag{2.5}$$

where d is distance from transmitter to receiver, η is path loss exponent that measures the rate at which the RSSI decreases with distance, X_σ is zero mean Gaussian distributed random variable whose mean value is *zero* and it reflects the change of received signal power in certain distance, d_0 is reference distance and usually equal to *one* meter, $P_r(d_0)$ is the calculated power at a reference distance d_0 from the transmitter.

Most of the chips which provide RSSI measurement show the relation of transmission power and receiving power by the formula [20] as given below:

$$P_r = \frac{P_t}{d^\eta} \tag{2.6}$$

From the above equation we get,

$$P_r(dBm) = A - 10 \cdot \eta \cdot log(d) \tag{2.7}$$

where P_r is the received signal power, A is signal power at a distance of one meter.

Using the above equation we can easily calculate the distance. Accuracy of RSSI depends on the path loss model. This is because RSSI is affected by fast fading, mobility, shadows, terrain. Savarse *et al.* [21] reported that the range error introduced by RSSI is $\pm 50\%$. This can be reduced by taking mean of the number of measurements at some distance. The improper calibration of cheap radio transceiver also affects the RSSI calculation. RSSI behaviour at different values of η is shown in Figure - 2.3.

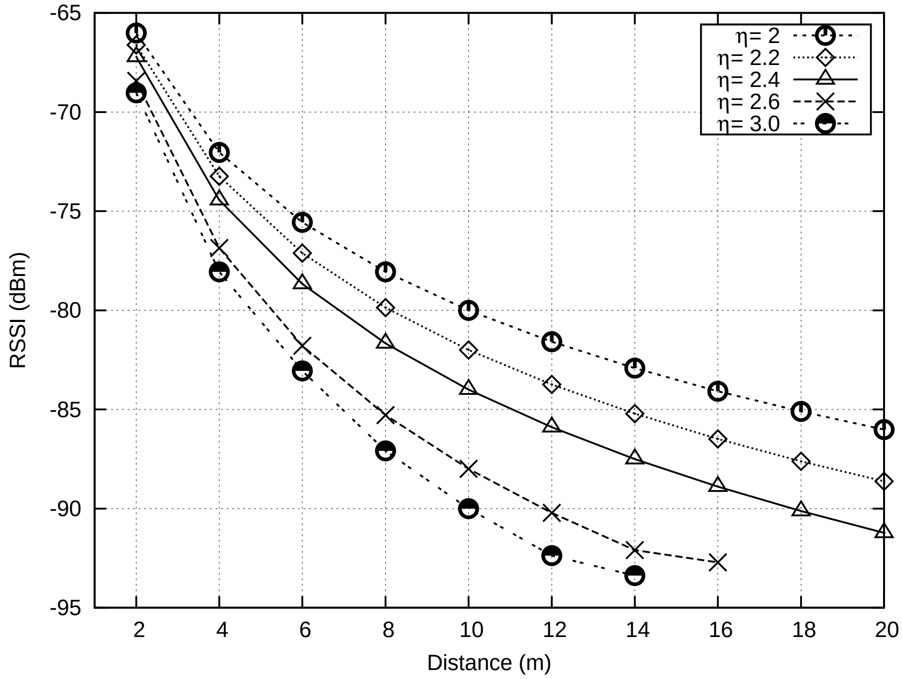


Figure 2.3: Effect of path loss exponent on RSSI with distance.

2.1.4 Angle/Direction of Arrival

Angle of Arrival (AoA) determines the direction/angle of propagation of received signal. It uses radio or microphone arrays to estimate the direction of transmitting node. TDoA at individual elements of the array is measured to estimates the direction. Analyzing the delay (phase or time difference) at each element, AoA is calculated.

Usually, a sensor is associated with two or more extra components such as antennas for radio signals, microphones for acoustic signals. Location of each component with respect to the sensor is known. In Figure - 2.4 to estimate AoA a four element Y shaped micrphone is used. AoA is estimated from the difference in arrival time of signal at each of the array element.

Disadvantages of AoA includes: (*i*) Hardware cost - each node must have one speaker and several microphones/antenna array. This increases cost as well as the size of node. (*ii*) Does not scale well for networks with higher number of nodes. (*iii*) Need very high resolution clock to produce result of acceptable accuracy. A qualitative comparison of these range based methods is shown in Table - 2.1.

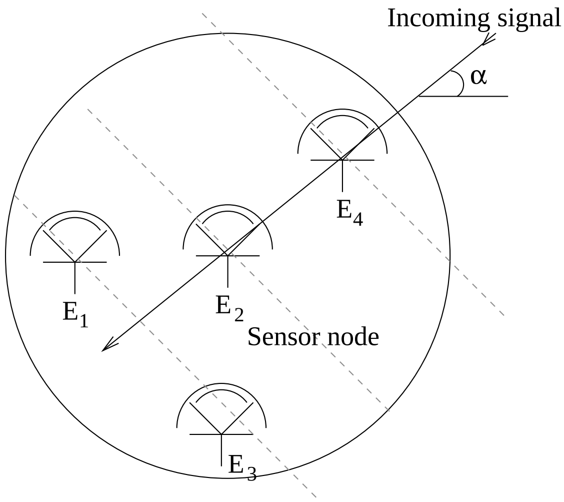


Figure 2.4: Angle of Arrival.

Techniques	Addational Hardware	Issues	Precision
AoA [22]	Arrays of Microphone	Directivity, Shadowing	Few degrees
ToA [17]	None	Synchronization	Centimeters (2 – 5 cm)
TDoA [22]	Speaker, Microphones	–	Centimeters (2 – 5 cm)
RSSI [19]	None	Interference	Meters (2 – 3 m)

Table 2.1: A qualitative comparison of range based localization techniques.

2.1.5 Hop Count

Sensor are deployed in a fashion such that each node remains in the range of its neighbour nodes, that is a node lies within the range R of its neighbouring node. Knowing the number of hops (*hopcount*) and length of one hop (*hoplength*) the distance d between any two nodes is computed as

$$d = (hopcount) \times (hoplength) \tag{2.8}$$

In the above formula, *hoplength* may vary, because a node may remain at any location within the range R. Therefore, *hoplength* may give erroneous result. However, Kleinrock and Silvester [23] have proposed a better estimation of *hoplength* if the expected number of neighbours/node (n_{local}) is known. This is given as below:

$$hoplength = R[1 + e^{-n_{local}} - \int_{-1}^{1} e^{(n_{local}/\pi) arccos t - t\sqrt{1-t^2}} dt] \tag{2.9}$$

Nagpal *et al.* [24] have shown that the above computation works well when $n_{local} > 5$. For measuring distance hop count is the best metrics. However, hop count metric has some limitation. They are: (i) Nodes not forming convex-hull may fail to find accurate $hopcount$. This is because of obstacles in shortest path to neighbour as shown in Figure - 2.5, and (ii) Distance measurement is always multiples of $hoplength$.

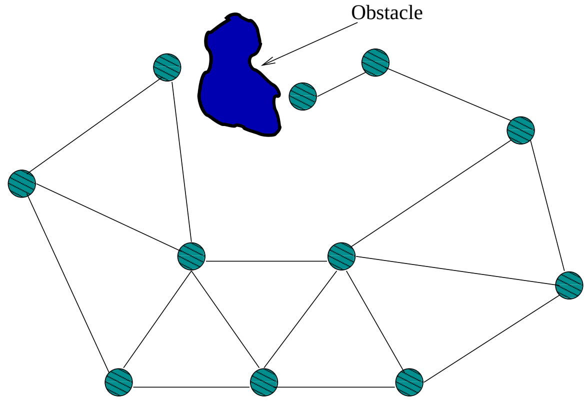


Figure 2.5: Distance estimation using hop count.

2.2 Position Calculation

Techniques used to estimate a node's location are trilateration, multilateration, and triangulation. Estimated distance and the position of anchor nodes is used to estimate a node's location.

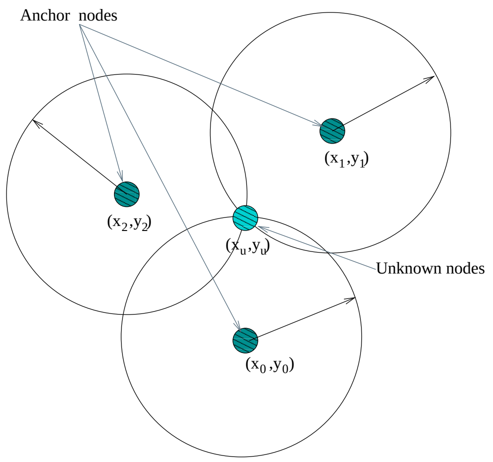


Figure 2.6: Trilateration

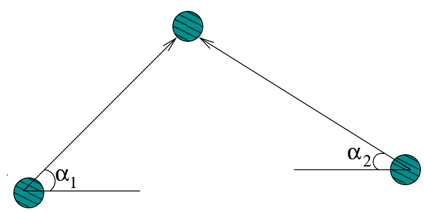


Figure 2.7: Triangulation

2.2.1 Trilateration/Multilateration

Trilateration is a geometric technique used to determine the location of an unknown node with the help of *three* location aware nodes/anchor nodes. It uses distance between the anchor nodes and the unknown node. A pictorial view of this geometric technique for localizing an unknown node (x_u, y_u) with anchor nodes (x_i, y_i) is shown in Figure - 2.6. Distance measurements are never perfect. As a result it is difficult to get an accurate location. Distance measurement from more than three anchors is known as *multilateration*. This technique can be used to get a unique location.

We illustrate multilateration in a 2-dimensional space with known distances between anchor nodes and an unknown node as

$$d_1^2 = (x_1 - x_u)^2 + (y_1 - y_u)^2 \tag{2.10}$$

$$d_2^2 = (x_2 - x_u)^2 + (y_2 - y_u)^2 \tag{2.11}$$

$$\vdots$$

$$d_n^2 = (x_n - x_u)^2 + (y_n - y_u)^2 \tag{2.12}$$

Subtracting equation (2.10) from (2.11) .. (2.12) gives

$$d_2^2 - d_1^2 = x_2^2 - x_1^2 - 2(x_2 - x_1)x_u + y_2^2 - y_1^2 - 2(y_2 - y_1)y_u \tag{2.13}$$

$$d_3^2 - d_1^2 = x_3^2 - x_1^2 - 2(x_3 - x_1)x_u + y_3^2 - y_1^2 - 2(y_3 - y_1)y_u \tag{2.14}$$

$$\vdots$$

$$d_n^2 - d_1^2 = x_n^2 - x_1^2 - 2(x_n - x_1)x_u + y_n^2 - y_1^2 - 2(y_n - y_1)y_u \tag{2.15}$$

Rearranging, (2.13) .. (2.15) in matrix form, we obtain

$$\begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ \vdots & \vdots \\ x_n - x_1 & y_n - y_1 \end{bmatrix} \begin{bmatrix} x_u \\ y_u \end{bmatrix} = \frac{1}{2} \begin{bmatrix} x_2^2 + y_2^2 - d_2^2 - (x_1^2 + y_1^2 - d_1^2) \\ x_3^2 + y_3^2 - d_3^2 - (x_1^2 + y_1^2 - d_1^2) \\ \vdots \\ x_n^2 + y_n^2 - d_n^2 - (x_1^2 + y_1^2 - d_1^2) \end{bmatrix}$$

Above matrix can be rewritten as

$$Au = b \tag{2.16}$$

where

$$A = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ \vdots & \vdots \\ x_n - x_1 & y_n - y_1 \end{bmatrix}, \; u = \begin{bmatrix} x_u \\ y_u \end{bmatrix}, \; b = \frac{1}{2} \begin{bmatrix} x_2^2 + y_2^2 - d_2^2 - (x_1^2 + y_1^2 - d_1^2) \\ x_3^2 + y_3^2 - d_3^2 - (x_1^2 + y_1^2 - d_1^2) \\ \vdots \\ x_n^2 + y_n^2 - d_n^2 - (x_1^2 + y_1^2 - d_1^2) \end{bmatrix}$$

Therefore, u can be derived as

$$u = (A^T A)^{-1} A^T b$$

2.2.2 Triangulation

Triangulation is a geometric technique that uses the trigonometry laws of *sine* and *cosines* on the angles of incoming signal α to estimate a unique location. A geometric computation of this is shown in Figure - 2.7.

AoA measurement requires bulkier and expensive hardware such as multi-sectored antennae. This makes triangulation unsuitable for small sensor nodes.

2.3 Localization algorithm

Localization algorithm is the last and most important stage of localization system. It utilizes the information collected in previous two stages. It defines how this information can be transformed to localize sensor nodes cooperatively. Cooperative localization refers to the collaboration between sensor nodes to find their locations. Mostly, accuracy of this stage is effected by the ranging method, deployment environment, and the relative geometry of unknown nodes to the anchor nodes.

Broadly, localization algorithms in WSNs can be divided into two categories: (i) *centralized*, and (ii) *distributed*. Centralized localization requires the migration of internode ranging and connectivity data to a sufficiently powerful central base station and then the migration of resulting locations back to respective nodes [25]. Centralization allows an algorithm to undertake much more complex mathematics than is possible in a distributed setting. Whereas in distributed localization, all the relevant computations are done on the sensor nodes themselves and the nodes communicate with each other to get their positions in a network.

On the basis of ranging method used, localization algorithms for WSNs can be broadly categorized into two types: (i) *range based*, and (ii) *range free*. Range based localization algorithms use the range (distance or angle) information from the beacon node to estimate the location [26]. Several ranging techniques exist to estimate an unknown node distance to three or more beacon nodes. Based on the range information, location of a node is determined. Some of the range based localization algorithm includes: Received signal strength indicator (RSSI) [19], Angle of arrival (AoA) [22], Time of arrival (ToA) [17], Time difference of arrival (TDoA) [22].

Range-free localization algorithms use connectivity information between unknown node and landmarks. A landmark can obtain its location information using GPS or through an artificially deployed information. Some of the range-free localization algorithm includes: Centroid [27], Appropriate point in triangle (APIT) [28], and DV-HOP [29]. In centroid the number of beacon signals received from the pre-positioned beacon nodes is counted and localization is achieved by obtaining the centroid of received beacon generators. DV-HOP uses the location of beacon nodes, hop counts from beacons, and the average distance per hop for localization. A relatively higher ratio of beacons to unknown nodes, and longer range beacons are required in APIT [30]. They are also more susceptible to erroneous reading of RSSI.

Range-based algorithms achieve higher localization accuracy, at the expense of hardware cost and power consumption. Range-free algorithms have lower hardware cost and are more efficient in localization. A brief review of different localization algorithms proposed in the literature for wireless sensor networks is presented below.

Simic *et al.* [31] proposed a range free distributed localization algorithm, in which each unknown node estimate its position within the intersection of bounding box of beacon nodes. Also, they found optimal number of known nodes required to minimize the localization error in WSN based on network area, number of nodes, and communication range (r). In their proposed scheme a sufficient number of beacon nodes should be deployed in order to localize entire network. Whitehouse [32] showed that the technique proposed by Simic *et al.* [31] fails in the localization of non-convex network (nodes not present in convex-hull of beacons), and under noisy range estimate.

A distributed range free localization algorithm called as DLE is proposed by Jang *et al.* [33]. In this each normal nodes collects the location information of neighbouring beacon nodes and then calculate the estimative rectangle (ER) to estimate its location. To improve the accuracy in location estimation DLE uses certain rules to shrink the ER by using the relative location of normal and farthest beacon nodes. Basically accuracy of node ER is improved by discarding the area included in the communication range of farthest beacon node - which does not cover the normal node. But, this approach of reducing the ER sometimes over-discard the communication area which does not cover normal node and thus result to an estimative error while calculating the estimated location.

Jang-Ping *et al.* [34] proposed a distributed range free localization scheme (DRLS). DRLS uses the combinations of connectivity constraints gathered from anchors to reduce the scope of the estimative region in which a normal node resides after collecting beacons from anchors. An improved grid-scan algorithm is then used to derive a more accurate estimated location. Finally, a vector-based refinement scheme is used to further improve the accuracy of the estimated location. There are three phases in the DRLS algorithm. In the first phase, each sensor node exchanges beacons so as to collect connectivity constraints. In the second phase, each normal node uses the improved grid-scan algorithm to get its initial estimated location. In the third phase, the normal node uses the vector-based refinement scheme to improve the accuracy of its estimated location. But this accuracy in location estimation increases complexity due to high message exchanging.

Shang *et al.* [35] proposed a centralized, range based algorithm called MDS-MAP. It works by using the law of *cosines* and linear algebra to reconstruct the relative positions of the points based on pair-wise distances. MDS operate in two stages: In first stage, relative map of nodes is formed using pair-wise distance and in second stage relative map is transformed into the absolute map using few number of beacon nodes. MDS-MAP provides a higher degree of accuracy with a complexity of $O(n^3)$, where n is the number of nodes in the network. This method is suboptimal and it requires all pairwise distance measurements of sensors to produce the global solution. It is difficult to satisfy this requirement in sparse networks. A modified version of MDS-MAP called weighted MDS (WMDS)is presented in [36] to remove these limitations. It estimates the unavailable/missing distance (MD) measurements prior to employing the proposed method. The estimated positions are then used to update the MDs and this estimation process repeats in an iterative manner until a stopping criterion is met. However, convergence of WMDS has not been proven, and its computational complexity is high [37].

He *et al.* [30] proposed a distributed, range free localization algorithm called Appropriate Point in Triangle (APIT). In this each unknown node receive beacons from the neighbouring anchor nodes and then construct exhaustive set of triangles using these anchor nodes. APIT repeats Point in Triangulation (PIT) test with different combination of triangles to narrow down the nodes estimative region. It uses a grid-scan algorithm to derive the intersection region of all the triangles using the PIT test and then sets the center of the intersection region as the estimated location of the normal node. APIT performs better under the high ratio of anchors. But, as the network area is divided into large number of small square grids; memory requirements by grid-scan algorithm to store the value of grid array is increases. Hence make it inappropriate for memory constrained sensor nodes.

Chandrasekhar *et al.* [38] proposed centralized, range free area based localization scheme (ALS). In this scheme, anchor nodes transmit signal at different power levels and each unknown node records the lowest power level corresponding to each neighbouring anchor node. As soon as an unknown node records power levels of *four* anchor nodes, it sends the recorded vector to a sink node (powerful node). Sink then decides in which region the reporting node lies and retransmit the same information to the reporting node.It provides a coarse location estimate of a sensor within a certain area, rather than its exact position.

Hasebullaha *et al.* [39] proposed a localization algorithm using a single anchor node and considered both the coarse grained, fine grained scenarios. In coarse grained, anchor nodes are equipped with larger number of antennas in order to cover full network area. In fine grained, beacon node is equipped with only one antenna, which rotates at a constant angular velocity. In the technique proposed by Kumar and Varma [40] sensor nodes are equipped with directional antenna in order to determine the angle (position) with respect to anchor node.

Zhang and Yu [41] proposed a distributed, range free localization algorithm called LSWD, in which unknown nodes are equipped with omni-directional antenna and a single mobile beacon node is equipped with a directional antenna. The mobile beacon node moves through the sensor area and transmit beacons (beacon node coordinates and time-stamp when the beacon is broad-casted) to sensor nodes for localization. Based on the collected beacon messages sensor nodes determine their locations by using the geometric characteristics of the confined area. To localize nodes correctly LSWD uses three different methods which include: (*i*) the greatest gain direction line intersection (GDDI), (*ii*) radiate region of intersection (RROI), and (*iii*) the border line intersection (BLI). Although, LSWD localizes nodes but it increases the cost of WSN as each node is equipped with an omni-directional antennae. Its efficiency depends on the trajectory taken by the mobile beacon node. Furthermore, with omni-directional antennae energy radiated in all directions can be easily interfared by wide range of environment noise. This may result in high localization error.

Khan *et al.* [42] proposed a distributed, iterative localization algorithm called DILOC, in m dimensional Eucledian space $\mathbb{R}^m$, that only requires only local communication. It exploits the structure of matrix resulting from the topology of communication graph of the network. For localization, it requires each node lies inside a convex hull of at least $(m + 1)$ anchor nodes. The location of each node can be computed iteratively by these $(m + 1)$ anchors. Basically, each node starts with a initial guess (random guess) of their position, and then update its location estimates as a convex combination. The coefficients o the convex combination are the barycentric co-ordinates of sensors with respect to their neighbours, which are determined from the Cayley-Menger determinants. These are the determinants of matrices that collect the local internode distances. Main problem with DILOC algorithm is that normal nodes outside the convex hull of the anchor nodes are unable to be localized.

Lee *et al.* [43] proposed a localization algorithm termed multiduolateration localization (MDL) and grouping multiduolateration localization (GMDL) for indoors by employing jumper setting of nodes. Their algorithm operate in two stages: First, edge nodes are localized using internal division and then the remaining surface nodes, are localized using localized edge nodes. It uses four beacon nodes placed at the corners of field. Localization accuracy of MDL and GMDL depends on the localization of edge nodes. It results in more error propagation as one wrongly localized edge node affects location estimation of all those surface nodes which use it as a reference node.

Antonio *et al.* [44] proposed a fully decentralized, range based algorithm that allows individual wireless nodes to iteratively refine the estimate of their position. It is based on the combined use of convex and non-convex optimization procedures. The algorithm starts with initialization phase where unknown node gather coordinates of adjacent anchor nodes and corresponding distances to them. Then, it performs a convex minimization using a gradient descent technique. This iterates until cost of the new position reaches a proper threshold close to zero. After this a refinement step by means of *vertex search heuristic* is accomplished. In vertex search heuristic, a minimum non-convex cost is searched among all intersections and the selected intersection is chosen as the final node position. This scheme ensure sensors qualifying the convex hull constraint to be globally convergent, but the converged solution suffer from significant gap in estimation performance as compared to optimal solution [45].

Shouhong *et al.* [45] proposed a distributed cooperative localization scheme and several iterative self-positioning algorithms. They are: (*i*) 'Pulled only' - on running this algorithm iteratively at all the sensors of the considered network, it leads to global convergence in the sense of the global convex cost it minimizes. But, in the presence of measurement errors it does not result in the global convergence. (*ii*) 'Pulled or Pushed' - on iteratively running this algorithm on all the sensors of the considered network, it suffers from the local convergence. But once correctly converged, resulted solution would be the least-square solution. (*iii*) A combined version that switches between the former two algorithms iterations independently at individual sensors based on locally collected information. It converges globally to the least-square solution, as long as the measurement errors are sufficiently small. Efficiency of this algorithm is heavily affected by measurement errors and it fails to localize nodes outside the convex hull of reference nodes.

2.4 Summary

In this chapter, we discussed about the localization system. We also discussed different components employed for localization. A brief review of different localization techniques for static WSNs is discussed.

In the next chapter, we proposed a localization technique for static WSN, where nodes are deployed in a grid pattern.

Chapter 3

Localization Using Single Anchor Node

Localization of nodes in a sensor network is essential for the following two reasons: (i) to know the location of a node reporting the occurrence of an event, and (ii) to initiate a prompt action whenever necessary. Different localization techniques have been proposed in the literature. Most of these techniques use three anchor nodes for localization of an unknown node. Increasing the number of anchor nodes will increase the overall cost of WSN. This is because GPS enabled nodes need frequent battery replacements or a battery of large capacity. Furthermore, GPS does not work well in indoors and dense areas/forests. Localization techniques also differ from environment to environment. In this chapter, we proposed a localization technique for grid environment. Sensor nodes are deployed in a grid pattern and localization can be achieved using a single location aware or anchor node.

3.1 Proposed Technique

In this section, we proposed a distributed range based localization algorithm for a grid environment. Since, a single anchor node is used for localization, we call this technique as localization using single anchor node (LUSA). We made the following assumptions:

(a) Sensors are deployed in a grid pattern as shown in Figure - 3.1.

(b) We identify three types of node: (i)*Beacon node:* A node which can locate its own position, and is usually equipped with GPS, (ii) *Special node:* Nodes which are perpendicular to the beacon node, and can determine their co-ordinates with respect to beacon node. For every beacon node there exist two *Special nodes*, (iii) *Unknown node:* Nodes which are un-aware of their location. They use localization algorithm to determine their position. Special nodes are treated as unknown nodes.

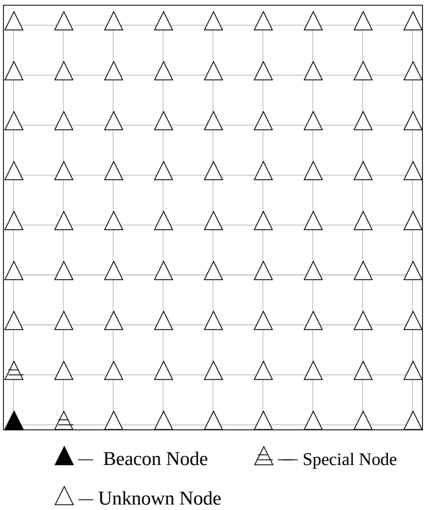


Figure 3.1: Deployment of Beacon node, Special node and Unknown node in a grid.

For localization, the beacon node initially broadcast its location information. *Special nodes* compute their distance from the beacon node using RSSI and determine their co-ordinates with respect to the beacon node. After computing their location information, *Special nodes* also act as beacon node. *Unknown nodes* use trilateration mechanism to compute their location information. We illustrate the localization process in the proposed

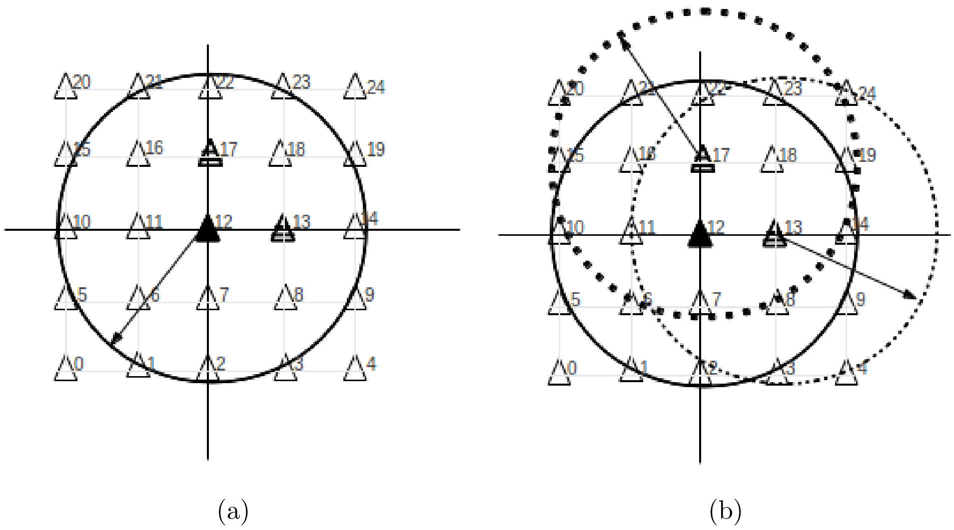


Figure 3.2: Localization in LUSA.

scheme using Figure - 3.2. Let node 12 in the figure is a beacon node, node 13 and 17 are special nodes, and the remaining nodes are unknown nodes. Initially, node 12 broadcast its position. This is received by the special nodes 13 and 17 along with other unknown nodes within the transmission range of node 12 as shown in Figure - 3.2(a). Nodes 13,

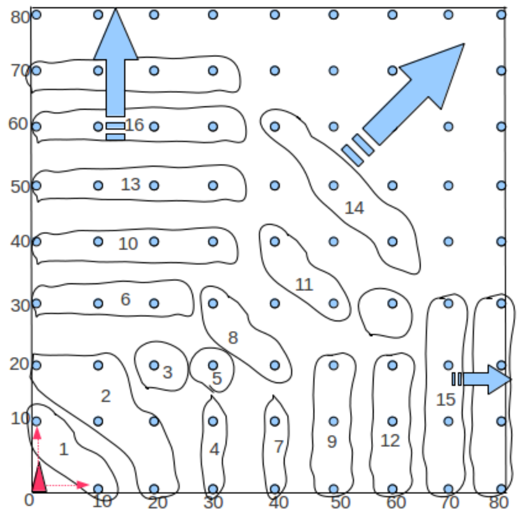


Figure 3.3: Localization pattern.

and 17 calculate their distance with respect to node 12, and localize themselves. At this stage all the nodes within the transmission range of node 12 has the position estimate of beacon node 12. In next stage, node 13 and 17 act as beacon nodes and broadcast their estimated position, as shown in Figure - 3.2(b), which is received by nodes 7, 8, 11, 14, 18, 22, and 23. These nodes localize themselves using trilateration. As more and more nodes gets localized, they act as beacon nodes. Above process continues until the whole network is localized. Figure - 3.3 shows the progress of localization in the proposed scheme in a 9×9 grid environment. Nodes encircled with same numerical value are likely to get localized at the same time instant.

3.2 Simulation Results

We have simulated the proposed scheme using Castalia simulator that runs on top of Omnet++. Transmitting power of nodes is considered to be -5 dBm (0.316 mW) so as to limit the communication range to 30 meters, and the path loss coefficient (η) to be 2.4.

A grid network of size 9×9 is considered for simulation. Metrics of interest are: (i) *Localization time*; and (ii) *Localization error* - which is computed as described below:

$$\overline{Error} = \frac{\sum_{i=1}^{N-R} ||\hat{\theta}_i - \theta_i||}{N-R}$$

where $\hat{\theta}_i$ is estimated position, θ_i is actual position, N is the total number of sensors in the network, and R is number of beacon nodes. We have considered the following two scenarios:

(i) Beacon node is placed at the corner of the grid as shown in Figure - 3.4, and (ii) Beacon node is placed at the middle of the grid as shown in Figure - 3.5. In each of the above scenarios there are one beacon node, two special nodes and many unknown nodes in the grid.

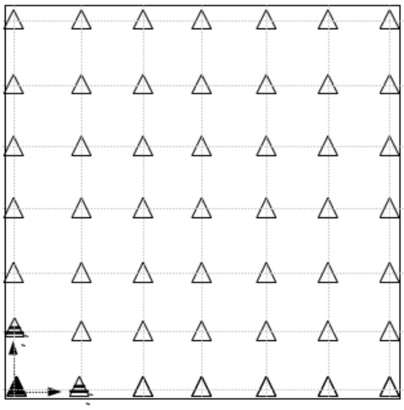


Figure 3.4: Beacon node at the corner of grid.

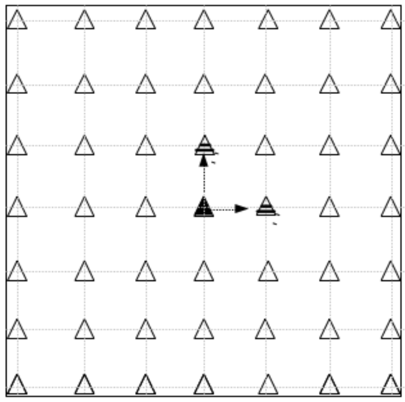


Figure 3.5: Beacon node at the middle of grid.

Location of Beacon node	Localization Time (s)	Localization Error (m)
At Corner	4.636377959069	0.000175
At Middle of grid	3.422031239100	0.001892

Table 3.1: Evaluation of proposed algorithm, placing the beacon node at two different places within the network.

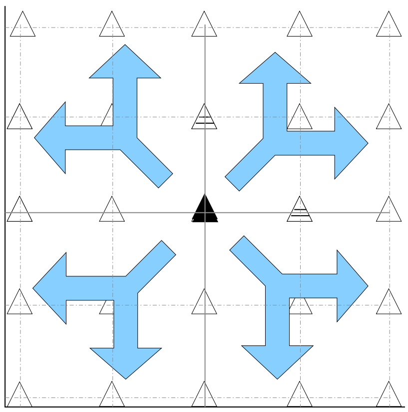


Figure 3.6: Process of localization when the beacon node is placed at the middle of the grid.

The time for localization and the average localization error in the above two scenarios is shown in Table - 3.1. It is observed from the Table - 3.1, that localization error when the beacon node is at the corner of grid is lower in comparison to placing at the center of the grid.

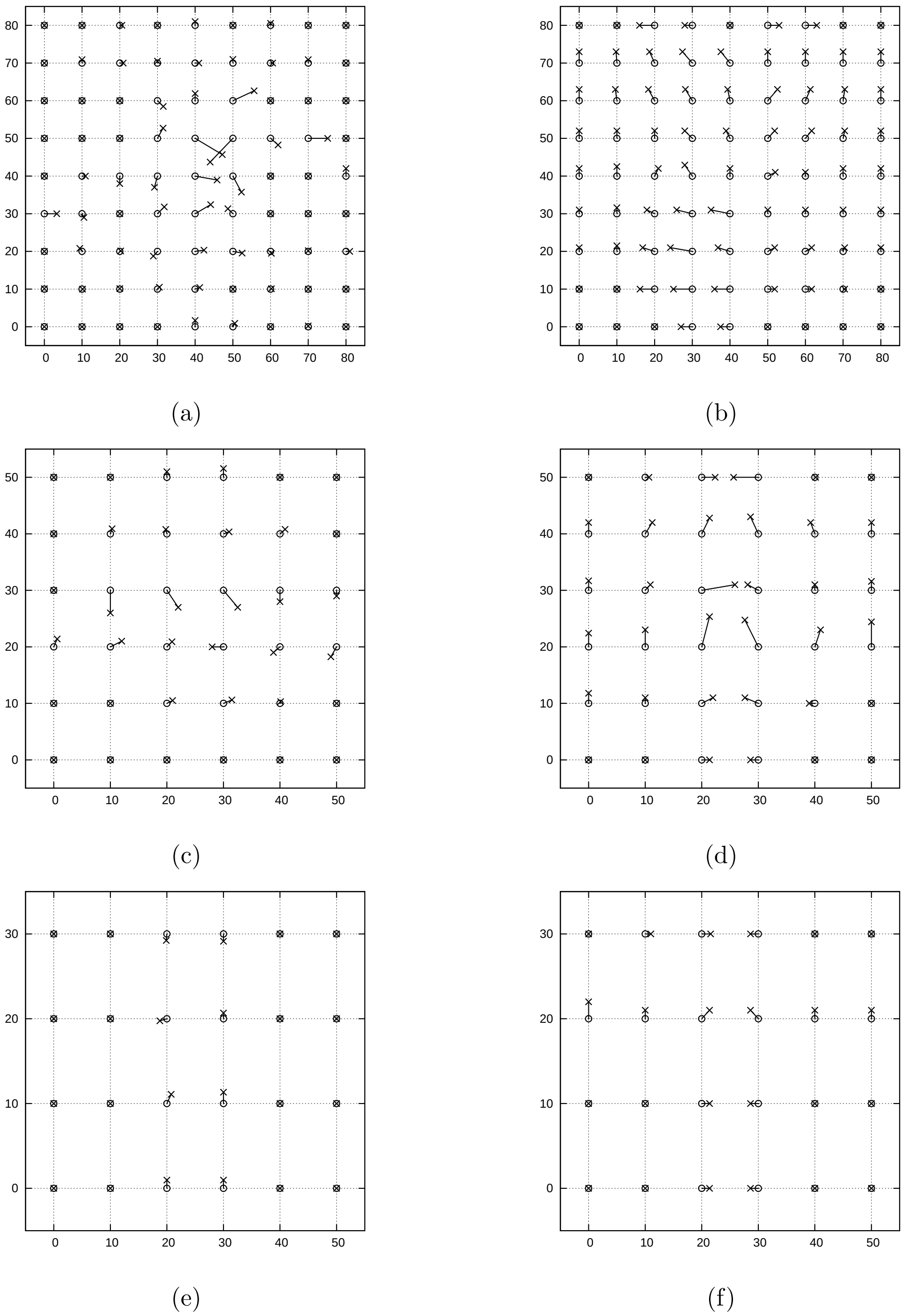
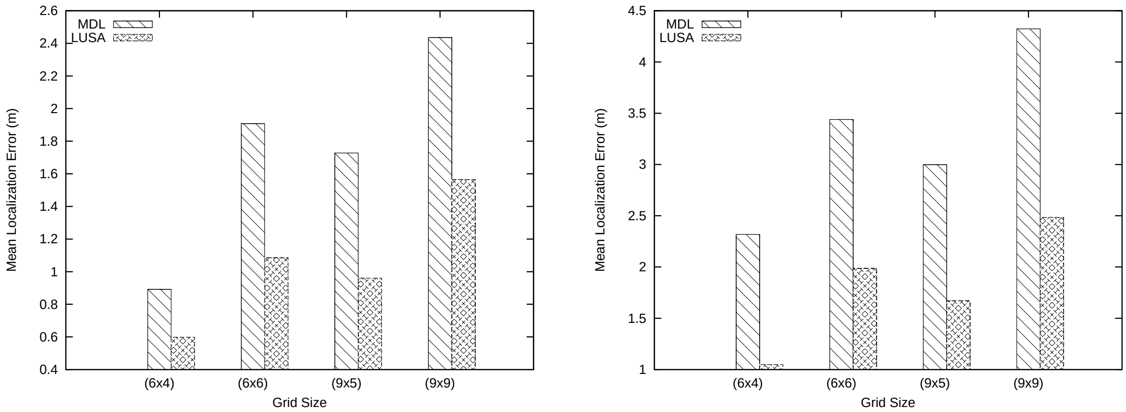


Figure 3.7: Distribution of localization error without interference in LUSA and MDL.

Localization proceeds parallely in four quadrants as shown in Figure - 3.6 when the beacon is placed at the center of the grid. As a result of parallel localization process, *localization error* propagates in more than one direction resulting in increase in the average localization error.

Next, we have compared LUSA with Multiduolateration (MDL). This is because MDL closely resembles with LUSA. MDL is proposed for a grid environment. It works using internal division. First, it localizes the edge nodes and then the remaining surface nodes. In MDL, four beacon nodes are placed at the four corners of the grid. For comparison with MDL, we also placed four beacon nodes at the four corners of the grid in LUSA. Metrices considered for comparison are localization time and localization error. a two scenarios: (*i*) without intereference, and (*ii*) with intereference; and the following grid sizes: (*i*) Square grid of size: 9×9, and 6×6, and (*ii*) Rectangular grid of size: 6×4, for comparison.



(a) (b)

Figure 3.8: Mean localization error (meters) in various grid: (a) Without interference, (b) With interference.

3.2.1 Localization Error

The geographical distribution of error without interference in LUSA and MDL for different grid size is shown in Figure - 3.7. Distribution of error in LUSA is shown in Figure - 3.7(a), 3.7(c), 3.7(e) and MDL in Figure - 3.7(b), 3.7(d), 3.7(f) for grid size of 9×9, 6×6, and 6×4 respectively. In each figure - dot '•' represents actual position of node and symbol '×' represents corresponding estimated position. The line joining '•' and '×' represents the magnitude of error. From Figure - 3.7, it is observed that LUSA has lower localization error than MDL. Higher localization error in MDL is attributed to the localization of surface nodes. Each surface node localize itself on the basis of four nearest edge nodes (left, right, above, below) using internal division. Localization of each surface node is independent of other surface nodes and depends solely on the edge nodes. Therefore, if any of the edge node do not get its exact location, it affects the location estimation of all surface nodes making use of that edge node for location estimation. We have shown the mean localization error in the corresponding grids for LUSA and MDL in Figure - 3.8(a).

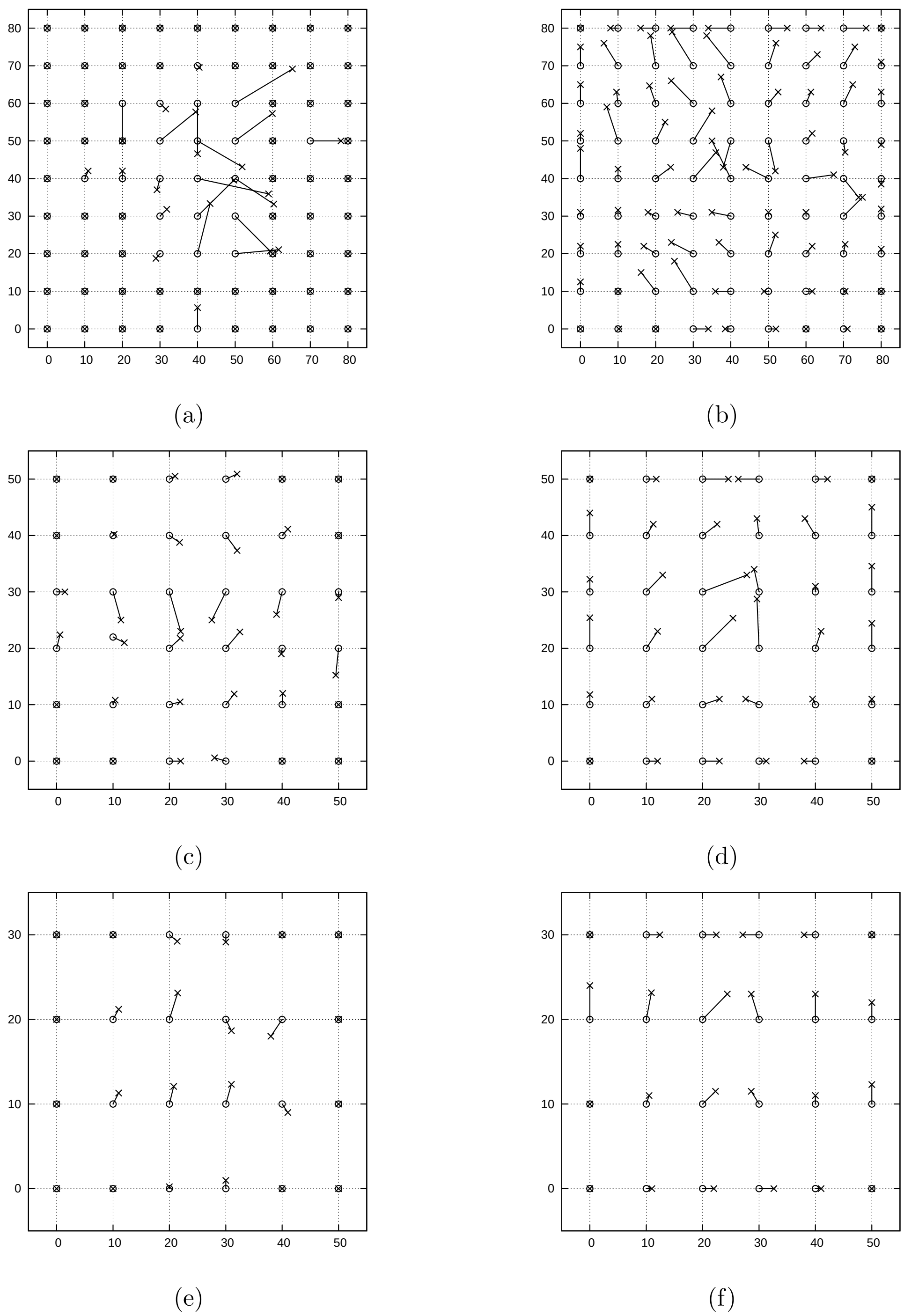


Figure 3.9: Distribution of localization error with interference in LUSA and MDL.

Next, we consider the effect of interference on location estimation. Effect of interference in LUSA and MDL is shown in Figure - 3.9 where Figures - 3.9(a), 3.9(c), 3.9(e) corresponds to LUSA and Figures - 3.9(b), 3.9(d), 3.9(f) corresponds to MDL in a grid size of 9×9, 6×6, and 6×4 respectively. Effect of interference on the localization error in grid of different size is shown in Figure - 3.8(b). It is observed that MDL is heavily affected in the presence of interference as compared to LUSA.

3.2.2 Localization Time

Localization time of LUSA and MDL for different grid size is shown in Figure - 3.10. Higher localization time in MDL is attributed to the localization of surface nodes. In MDL, localization proceed in two stages : (i) First, it localizes the edge nodes, and (ii) Next, it localizes the remaining surface nodes. In the second stage, each surface node select a reference edge node based on shortest path. This contributes to higher localization time. Whereas, in LUSA, localization of node's proceeds simultaneously and does not put any constraint on the selection of reference nodes.

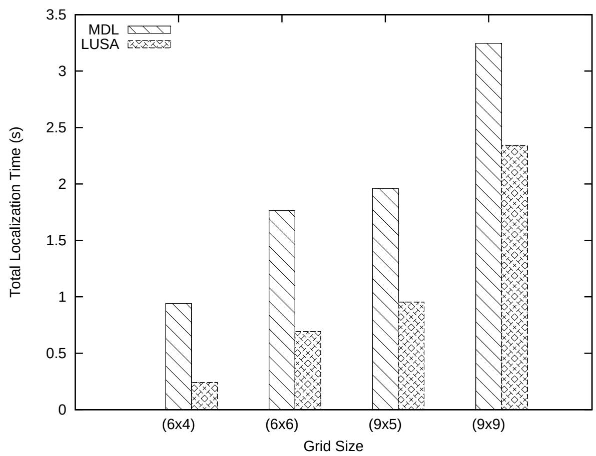


Figure 3.10: Localization Time.

3.3 Summary

In this chapter, we proposed a localization method for grid network called LUSA. In LUSA three types of nodes are identified. They are anchor, special and unknown nodes. For every anchor there are two special nodes and they are placed perpendicular to the anchor node. Localization in LUSA is achieved using a single beacon node and two special nodes. LUSA is compared with MDL, which is also a localization technique proposed for grid network. It is observed that the proposed scheme has lower localization error and lower localization time in comparison with MDL.

Chapter 4

Distributed Binary Estimation Approach

4.1 Introduction

Most of the existing localization techniques use three or more anchor nodes for localizing a single unknown node except for those schemes where directional antenna is used. In the scheme using directional antenna [39] algorithmic complexity, size and cost of node is more. In this chapter, we propose a range based localization algorithm for sensor networks in a grid environment. The proposed technique localizes an unknown node using two anchor/location-aware nodes.

4.2 Distributed Binary Node Localization

In this section, we proposed a node localization technique called Distributed Binary Node Localization Estimation (DBNLE). The proposed localization technique is distributed in nature. We call it binary, because each unknown node other than the edge nodes (placed with respect to anchor node) use two location aware nodes in the localization process. The following assumptions are made in DBNLE:

(i) Nodes are deployed in a grid.

(ii) Distance between the grid points are set as per the RSSI requirement.

(iii) Nodes are classified into three types: (a) *Anchor node*: Nodes whose position is known either through GPS or manually built-in. In DBNLE there is one anchor node. (b) *Unknown node*: Node which use localization technique to determine its position. (c) *Settled node*: These are the nodes that have obtained their location information through a localization technique. They serve as an anchor node for the remaining unknown nodes. Deployment of nodes in a grid is shown in Figure 4.1.

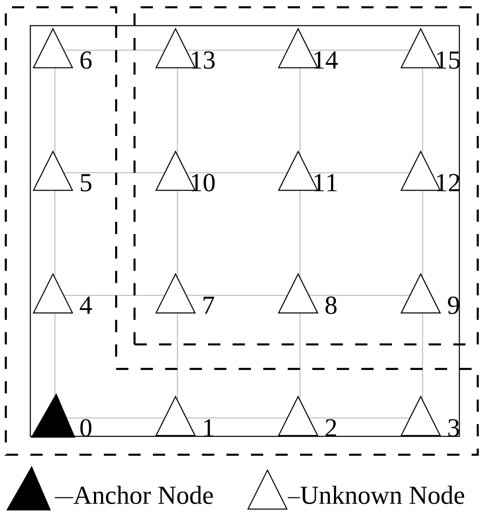


Figure 4.1: Deployment of nodes in a grid, showing the placement of anchor and unknown nodes.

DBNLE operate in three phases: *(i) First phase*: Edge nodes with respect to anchor node get localized and become settled nodes, *(ii) Second phase*: Settled nodes broadcast their position, and *(iii) Third phase*: Unknown node gets localized after obtaining position and range measurements from any two settled nodes. Phase Two and Three continues until all nodes get localized. Localization of edge nodes is explained in Subsection 4.2.1 and the remaining unknown nodes in Subsection 4.2.2.

4.2.1 Localization of Edge nodes

Lines $13-16$ in Algorithm 1 explain localization of edge nodes. We consider Figure 4.1 to illustrate localization of edge nodes. In Figure 4.1, node 0 is the anchor node, and nodes $1, 2, 3, 4, 5,$ and 6 are the edge nodes. Let (x_0, y_0) be the location of anchor node 0. On receiving location information from the node 0, node 1, and node 4 gets localized. Node 1 compute its co-ordinate as follows:

$$x_1 = x_0 + distance\ between\ node\ 0\ and\ 1,$$

$$y_1 = y_0.$$

Node 4 compute its position as:

$$x_4 = x_0,$$

$$y_4 = y_0 + distance\ between\ node\ 0\ and\ 4.$$

Algorithm 1: DBNLE Localization algorithm

Input: $\mathcal{N}_{en}$: Edge node with respect to Anchor node, $\mathcal{N}_r$: Nodes other than $\mathcal{N}_{en}$, $\mathcal{A}$: Anchor node

```
1  beaconSet ← φ                                    /* Set of received locations */
2  rBeacon ← 0                                      /* Number of received beacons */
3  flag ← 0                                         /* Set to 1, if node gets localized */
4  dist[2] ← −1                                     /* Array for storing distances */
5  Initialization:
6  if n ∈ A then                                    /* If this is an anchor node */
7      Broadcast beacon
8  Input:
9  msg ← beacon
10 dist ← distanceEstimation(msg)
11 increment rBeacon
12 Action:
13 if n ∈ N_en then
14     estimate Position using msg and dist
15     broadcast beacon
16     flag ← 1
17 else if (n ∈ N_r) and (rBeacon < 2) then
18     beaconSet ← beaconSet ∪ msg
19     dist[rBeacon] ← dist
20     if dist[rBeacon] = dist[−−rBeacon] then      /* Check distance constraint */
21         delete dist[rBeacon]
22         delete recent msg from beaconSet
23         decrement rBeacon
24     if rBeacon = 2 then
25         estimate Position using dist[2] and beaconSet
26         broadcast beacon
27         flag ← 1
```

Description of Algorithm 1: *Localization in DBNLE starts with a beacon broadcast by an anchor node as shown in lines 6 – 7. Lines 13 – 16 represent localization of edge nodes and simultaneously acting as settled nodes. Lines 17 – 27 represent localization of unknown nodes as soon as they receive beacons from two non-equidistant settled nodes.*

After computing their location information, node 1 and 4 become settled node. Node 2 and 3 gets localized as node 1 on receiving location information from node 1 and node 2 respectively. Node 5 and 6 gets localized as in node 4 on receiving location information from node 4 and 5 respectively.

4.2.2 Localization of Unknown nodes

In the proposed scheme an unknown node requires location information from two settled nodes for localization. An unknown node should not be equidistant from the two settled nodes considered for localization. Figure 4.2 shows the selection of settled nodes for localization. Figure 4.2(a) shows the wrong selection and Figure 4.2(b) shows the correct selection of settled nodes by an unknown node. On receiving the location information from two settled nodes, an unknown node compute the following: (i) Its distance from two settled nodes, (ii) distance between two settled nodes, (iii) the angle at which the position information of settled node was transmitted. For localization we consider only the angular information of settled node whose location information was received first. An unknown node selects two settled node for localization, which are not equidistant from it and computes the distance between them. To illustrate the localization of unknown nodes, we consider nodes 7 and 10 of Figure 4.1. Location information broadcast by node 0 is received by node 7 as shown in Figure 4.3(a). Let b_1 be the distance between node 7 and node 0, and θ_1 be the angle at which node 0 have transmitted beacon to node 7. Location information broadcast by node 1 is received by node 7, and let a_1 be the distance between node 7 and node 1. Let c be the computed Euclidean distance between node 0 and 1 at node 7.

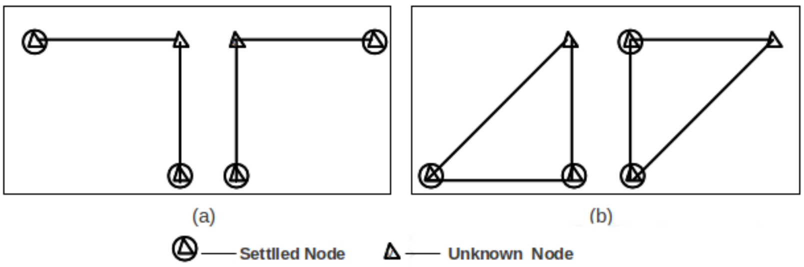


Figure 4.2: Selection of settled nodes for localization.

$$c = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2}$$

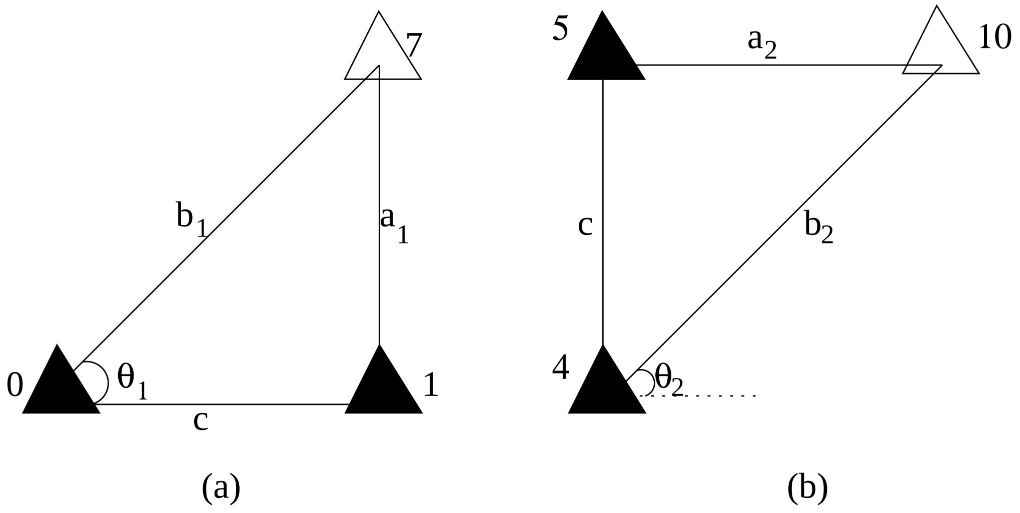


Figure 4.3: Localization of unknown nodes 7 and 10

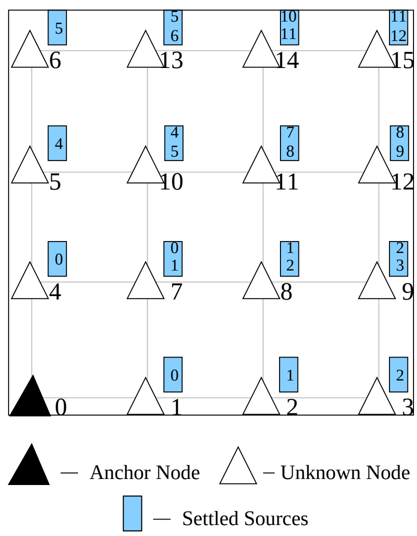


Figure 4.4: Nodes involved in the localization of unknown nodes in a 4 x 4 grid.

where (x_0, y_0) is the location of node 0, and (x_1, y_1) is the location of node 1. Similarly, unknown node 10 receives location information from nodes 4 and 5 as shown in Figure 4.3(b). Let θ_2 be the angle at which node 4 have transmitted beacon to node 10. The angle θ_1 and θ_2 is computed as follows:

$$\theta_1 = cos^{-1}((b_1{}^2 + c^2 - a_1{}^2)/2b_1c).$$

$$\theta_2 = 90^\circ - (cos^{-1}((b_2{}^2 + c^2 - a_2{}^2)/2b_2c)).$$

Let (x_7, y_7) and (x_{10}, y_{10}) be the co-ordinates of nodes 7 and 10 respectively. Node 7 compute its co-ordinate (x_7, y_7) as follows:

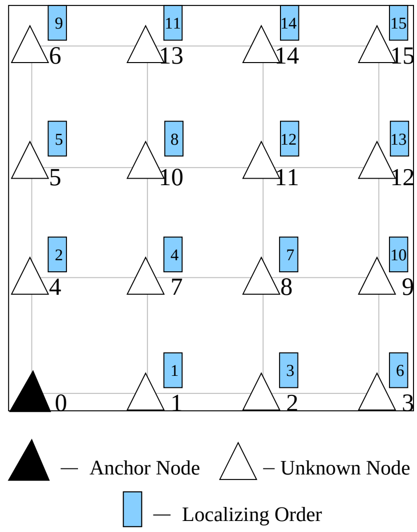
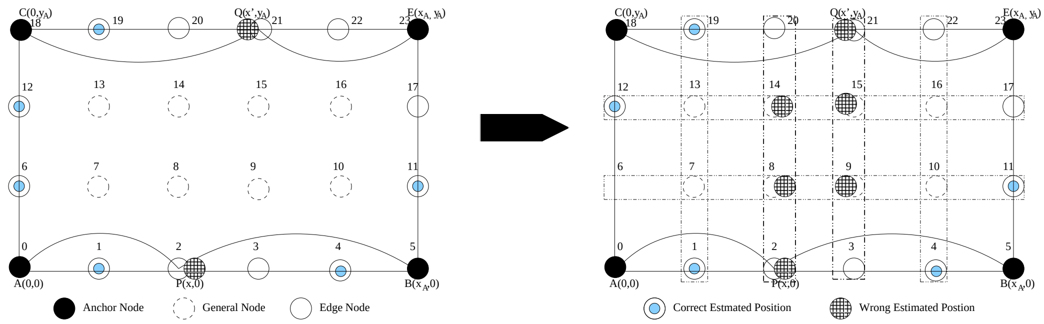


Figure 4.5: Localization pattern in a 4 x 4 grid.



(a) (b)

Figure 4.6: Localization process in MDL: (a) Localization of edge nodes, (b) Localization of surface nodes using nearest edge nodes.

$$x_7 = x_0 + b_1 * cos\theta_1$$
$$y_7 = y_0 + b_1 * sin\theta_1$$

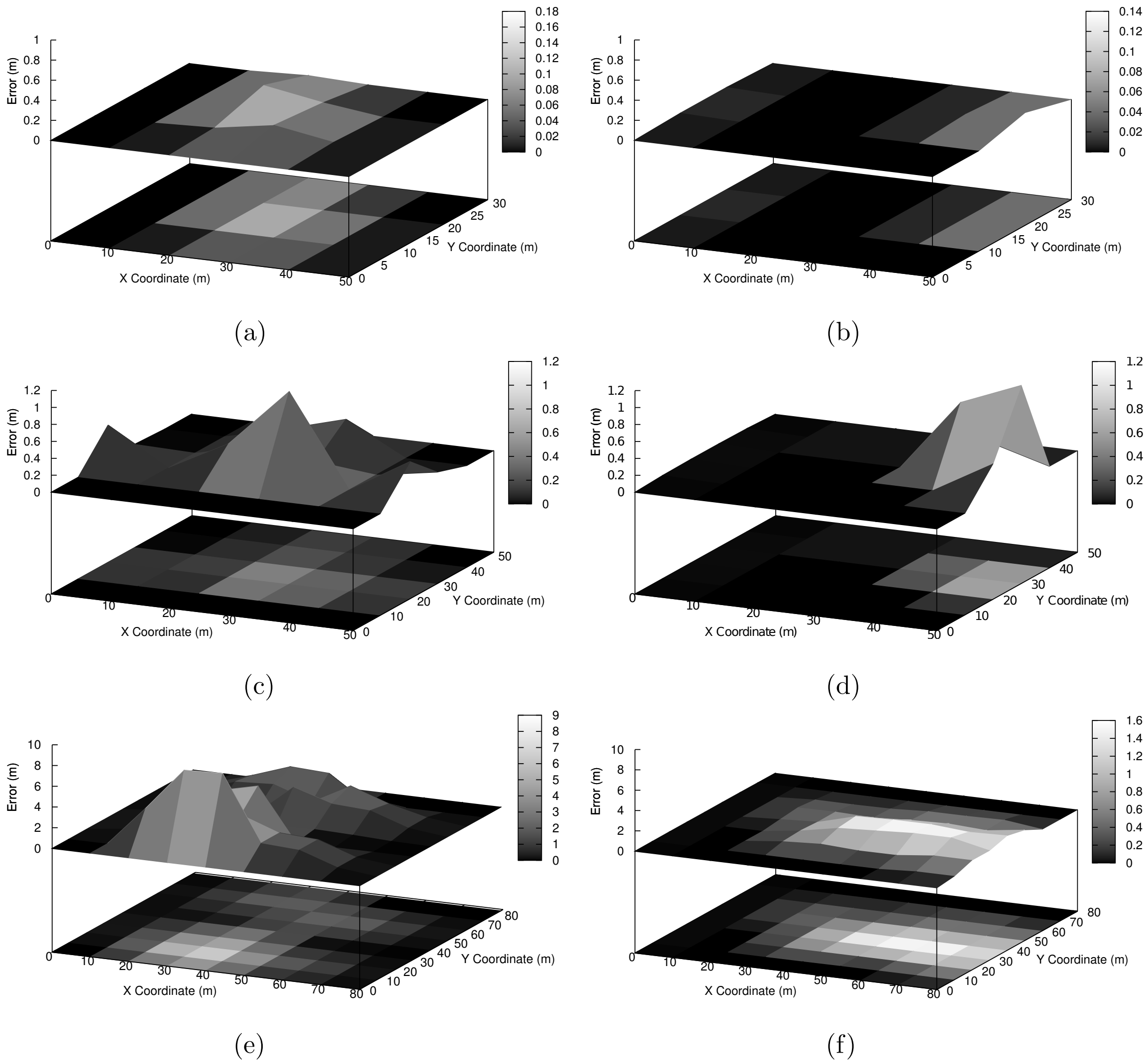
Similarly, node 10 compute its co-ordinates (x_{10}, y_{10}) as follows:

$$x_{10} = x_4 + b_2 * cos\theta_2$$
$$y_{10} = y_4 + b_2 * sin\theta_2$$

The above process continues until all nodes are localized. Figure 4.4 shows the progress of localization in a 4×4 grid. Rectangular box to the right of each node shows the settled nodes used for its localization. Figure 4.5 shows the localization pattern *i.e.*, the order in which unknown nodes are localized in a 4 x 4 grid. Rectangular box to the right of each node shows its corresponding localization order.

4.3 Simulation Results

We have simulated DBNLE, using Castalia simulator [46] that runs on the top of the Omnet++ and compared with a closely related scheme called Multiduolateration (MDL) [43]. Metrics considered for comparison are: *(i)* Accuracy in location estimation, and *(ii)* Time required for localization. Localization of MDL is shown in Figure 4.6. It works in two phases: *(i)* First phase: In this phase edge nodes are localized using internal division as



(a) (b) (c) (d) (e) (f)

Figure 4.7: Geographical distribution of error for a grid size of 6 × 4, 6 × 6, and 9 × 9 is shown in a, c, and e respectively for MDL and b, d, and f respectively for DBNLE.

shown in Figure 4.6(a), and *(ii)* Second phase: In this phase surface nodes are localized using four nearest edge nodes (left edge node, right edge node, above edge node, below edge node) as shown in Figure 4.6(b). Parameters considered for simulation are given below:

(i) Path loss coefficient (η) = 2.4.

(ii) Distance between successive nodes = 10 meters.

(iii) Number of anchors nodes = 4. They are placed at the corners of the grid.

RSSI technique is used for ranging. Grid of size 6 $\times$ 4, 6 $\times$ 6, 9 $\times$ 9 is considered for comparison.

4.3.1 Localization Error

The geographical distribution of error in MDL and DBNLE for grid of different size is shown in Figure 4.7. Distribution of error in MDL for grid size of 6 $\times$ 4, 6 $\times$ 6, 9 $\times$ 9 is shown in Figure 4.7(a), 4.7(c), 4.7(e) respectively, Distribution of error in DBNLE for the grid size of 6 $\times$ 4, 6 $\times$ 6, 9 $\times$ 9 is shown in Figure 4.7(b), 4.7(d), 4.7(f) respectively. Figure 4.7 depicts the distribution of location error, where the peaks indicate magnitude of error in estimated position vis-a-vis their real position. It is observed from the Figure that the magnitude of peaks are lower in DBNLE compared to that of MDL. This is because in MDL each surface node required location information from four edge nodes for localization. Any error in the localization of edge node, propagates to the surface nodes to a greater extent.

Figure 4.6 illustrate the error propagation in MDL. Suppose there is an error in the localization of edge nodes 2 and 21 as shown in Figure 4.6(a). Localization of node 15 requires the location information of edge nodes 3, 12, 17, and 21. Since there is an error in the localization of 21, this error contributes to the localization error of node 15. Similarly, node 9 will be wrongly localized. Localization error in node 2, leads to localization error in node 8 and 14. In DBNLE, an unknown node needs only two node for localization as compared to four nodes in MDL. As a result the cumulative error propagation is lesser in DBNLE.

4.3.2 Localization Time

Localization time refers to the time required for the localization of the whole network. Localization time of both MDL and DBNLE for different grid size is shown in Figure 4.8.

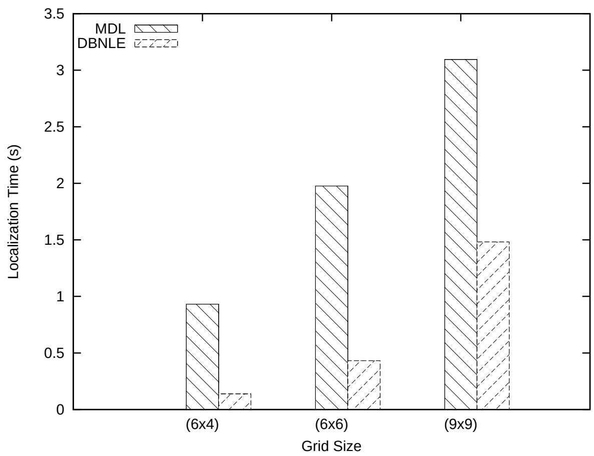


Figure 4.8: Localization time of MDL *vs.* DBNLE in different grid sizes.

It is observed that MDL takes more time for localization than DBNLE. This increase in localization time is attributed to the shortest path algorithm used by each surface node for the selection of its reference edge nodes.

4.4 Summary

In this chapter we proposed a localization method called distributed binary node localization estimation (DBNLE) for grid network. Three types of node are identified in DBNLE. They are: anchor node, settled node, and unknown node. For localization, an unknown node require two settled nodes. An unknown node becomes settled node after obtaining location information. Localization can be achieved using a single anchor node. DBNLE is compared with a similar scheme called multi-duolateration (MDL) also proposed for grid. It is observed that the DBNLE has lower localization error and localization time compared to MDL.

In the next chapter we proposed a localization technique for mobile WSN.

Chapter 5

Dead Reckoning Technique

5.1 Introduction

Mobility of sensor nodes increase the applicability of wireless wensor networks (WSNs). Mobility of sensor nodes with respect to environment can be of two types: *(i)* static, and *(ii)* dynamic. In both the case, sensor node is either fixed to a carrier like zebras in a zebranet [2], or placed on a robotic platform. In static case, a sensor node is only data driven, *i.e.*, to sense the environment and report to the base station (BS). In dynamic case, a sensor node is not only data driven, but also serve as an actuator. Whether it is static or dynamic, the position of nodes changes oftenly. As a result a node in mobile WSNs is localized more than once, compared to static WSNs - where a node is localized only once at the initialization of network. The continuous localization of nodes with mobility results in: *(i)* faster battery deletion and hence reduces the lifetime of sensor nodes, *(ii)* increase in the communication cost. On the contrary, mobility improves: *(i)* coverage of WSN - uncovered locations at one instant can be covered at some other instant of time, *(ii)* enhances the security - intruders can be detected easily as compared to the static WSNs, *(iii)* increases connectivity - mobility increases the neighbours of a node [13].

A mobile WSN can be in one of the following scenarios [15, 47–58]:

1. *Normal nodes are static, and seeds are moving*: In this scenario, mobile anchor nodes (≥ 1) continuously broadcast their location. As soon as a static node receives three or more than three beacons, it localizes itself. Accuracy and localization time depends mostly on the trajectory followed by the seeds.

2. *Normal nodes are moving, and seeds are static*: In this scenario, each normal node is expected to receive the beacons at the same instant of time. Otherwise, it will result in inaccurate estimated location. With time span the previous estimated location become

obsolete. As a result nodes localize repeatedly at fixed intervals with new received seed locations. One of the best example for this scenario is a battlefield, where normal nodes are attached to military personnel and seeds are fixed as landmarks within the battlefield. This not only helps in detecting the current position but also helps in providing feedback from a particular area of battlefield.

3. *Both the normal nodes and seeds are moving*: This scenario is the most versatile and complex among all the three. In this, the topology of the network changes very often. It is difficult for a normal node to get fine grained location. Therefore, the localization error is comparatively higher than the previous two scenarios.

In this chapter, we present a localization algorithm for third scenario, *i.e.*, for a network where all the nodes are mobile. We consider this scenario because: *(i)* a little emphasis has been given, owing to its complexity, *(ii)* to the best of our knowledge whatever little localization techniques has been proposed for this scenario have used the range free techniques only for estimating the distance between nodes. In the propose technique we have used a range based technique for distance estimation between the mobile nodes.

5.2 Related work

Although a rich literature is available for localization in static WSN, not enough attention has been drawn for the localization of mobile WSN, owing to the complexity added due to the node mobility. Most of the existing localization techniques for mobile WSN use Monte-Carlo localization (MCL) approach, which is not only time-consuming but also memory intensive. A brief review of different localization algorithms proposed in the literature for mobile sensor networks is presented below.

Tilak *et al.* [59] proposed two classes of localization approach: *(i)* Adaptive, and *(ii)* Predictive; for mobile WSNs considering the accuracy as well as energy requirement. Adaptive localization dynamically adjusts the localization period based on the recent observed motion of the sensor, obtained from examining the previous locations. This approach allows a sensor to reduce its localization frequency when it is slow, or increase when it is fast. In the predictive approach, a sensor estimate the motion pattern and project its motion in future. If the prediction is accurate, which occurs when nodes are moving predictably, location estimation may be generated without performing actual localization. This reduces the localization frequency thereby saving energy.

Bergamo and Mazzimi [51] proposed a range based algorithm for localizing mobile WSNs. They used fixed beacons which are placed in two corners on the same side of a rectangular space, whose signals are used by mobile sensors to compute their relative position. Sensors estimate their power level from the received beacon and estimate their position by triangulation method. They also studied the effect of mobility and fading in finding the accurate position.

Hu and Evans [15] proposed a range free technique based on Monte-Carlo localization (MCL). This technique is used for the localization of robots in a predefined map. It work in two steps: First, it represent the possible locations of an unknown node with a set of weighted samples and in the next stage, invalid samples are filtered out by incorporating the newly observed samples of seed nodes. Once enough samples are obtained, an unknown node estimate its position by taking the weighted average of the samples. In this technique, the sample generation is computationally intensive and iterative process. This also needs a higher density of seeds.

Aline *et al.* [60] proposed a scheme to reduce the sample space generated in [15]. They named it as Monte-Carlo Boxed (MCB) scheme. The sample generation is restricted within the bounding box, which is built using 1-hop and 2-hop neighbouring anchor nodes. The neighbouring anchor information is also used in the filtering phase. Therefore, it reduces the number of iterations to construct the sample set. However, the localization error in MCB is not reduced if the number of valid samples is same as that in MCL.

Rudafshani and Datta [61] proposed two algorithms called MSL and MSL* which are based on MCL technique. MSL* localizes mobile as well as static sensor nodes. It uses sample set of all 1-hop and 2-hop neighbours of normal nodes and anchor nodes. This resulted in better estimation of position with increased memory requirements and increased communication cost. In MSL, a node weight its samples using the estimated position of common neighbour nodes. MSL* outperforms MSL in most scenarios, but incurs a higher communication cost. MSL outperforms MSL* when there is significant irregularity in the radio range. Accuracy of common neighbour nodes is determined by their closeness value. Closeness value for a node P with N samples is computed as:

$$Closeness_P = \frac{\sum_{i=1}^{N} W_i \sqrt{(x_i - x)^2 + (y_i - y)^2}}{N}$$

where (x, y) is P's estimated position and (x_i, y_i) is P's i^{th} sample with weight W_i. Both MSL and MSL* need higher anchor density and node density. Also, when v_{max} (maximum velocity) is large, performance of both MSL and MSL* reduces to a greater extent. Furthermore, the size of bounding box for the generation of samples is reduced in [62], using the negative constraint of 2-hop neighbouring anchor nodes. This reduces the computational cost of obtaining samples, and a higher location accuracy is achieved under higher density of common nodes.

Wang *et al.* [63] proposed RSS based MCL scheme to sequentially estimate location of mobile nodes. First, it uses a set of samples with related weights to represent the posterior distribution of node's location. Next, it estimates the node's location recursively from the RSS measurements within a discrete state-space localization system. Accuracy of this scheme depends on the number of samples used and the log normal statistical model of RSS measurements. Comparison of these techniques is shown in Table 5.1.

PROPOSALS	Nature	Technique Used	Mobility Model	Comments
Tilak et al. [59]	Range Free	Triangulation	Random Waypoint Model, Gaussian Markovian Model	Foccused more on localization frequency.
Bergamo et al. [51]	Range Based	Triangulation	Random Waypoint Model (RWP)	Puts a limit on the localization area.
Evans et al. [15]	Range Free	Sequential MCL	Random Waypoint Model, Reference Point Group Model [64]	MCL does not converge fastly in slow WSN's.
Aline et al. [60]	Range Free	MCL Boxed	Modified RWP with pause time = 0 & minimum node speed = 0.1 m/s	Does not improve if no. of samples same as in MCL.
Datta et al. [61]	Range Free	Particle filtering approach of MCL	Modified RWP with pause time = 0 seconds	Computationally intensive & high communication cost.
Wang et al. [63]	Range Based	Sequential MCL	Random Waypoint Model	Accuracy depends on the quality of samples used and RSSI model.

Table 5.1: Comparison of different localization techniques for Mobile WSN's

5.3 Proposed Localization Technique

In this section, we propose a range based, distributed localization algorithm for mobile WSNs. The proposed technique is called Dead Reckoning Localization Technique (DRLMSN). In DRLMSN nodes are classified into the following three types: (*i*) *Anchor node* ($\mathcal{A}$): A node which can locate its own position, and is usually equipped with GPS, (*ii*) *Normal/unknown node* ($\mathcal{U}$): Nodes which are unaware of their location, and uses localization algorithm to determine their position, (*iii*) *Settled node* ($\mathcal{S}$): These are the normal nodes that have obtained their location information through a localization technique. They serve as an anchor node for the remaining unknown nodes.

To localize normal mobile nodes accurately with the help of mobile anchor nodes is a difficult task. This is because the transmitter as well as the receiver changes their position at every time instant. Therefore, to localize, a normal node must receive the *beacons* from all the neighbouring nodes at the same time instant. A *beacon* is the frequent advertisement from anchor/settled nodes. This advertisement contains the anchor/settled *node identify*, and *location*. Continuous localization of mobile nodes drains their battery power at a faster rate which ultimately reduces the lifetime of sensor nodes.

In DRLMSN, sensor nodes are localized during a time interval called *checkpoint*. There are two localization phases in DRLMSN. First phase is called *Initialization* phase. In this phase, a node is localized using trilateration mechanism. A node remains in the initialization phase until it localizes using trilateration mechanism. The subsequent localization phase is called *Sequent* phase. In this phase a node localizes itself using only two anchor nodes. Bézout's theorem is used to estimate locations of a node. A *dead reckoning* approach is used to identify their correct estimated position. Once a node is localized in either of the above two phases, it act as settled node and broadcasts a beacon during the checkpoint. Initialization and Sequent phases are explained below.

5.3.1 Initialization Phase:

During the *checkpoint*, each anchor node broadcasts a beacon. A normal node localizes itself for the first time during the checkpoint by using three anchor nodes. As soon as, a node localizes, it broadcasts a beacon during the same checkpoint. This results in the localization of one/two beacon deficit nodes. This process continues until the end of the checkpoint.

At the end of the checkpoint, some nodes fail to localize. The possible reasons for localization failure and the corresponding actions to be taken are: *i) A normal node receives only one (or two) beacon.* In this case, normal node deletes the received beacons and moves on. In the next checkpoint it attempt to localize using three beacons. *ii) A normal node receives no beacon.* In this case, a node moves on and tries to localize itself in the next checkpoint using three beacons.

5.3.2 Sequent Phase:

A node goes to the sequent phase after localization using trilateration mechanism. In this phase, each normal node localizes with only two nearest location aware nodes (*anchor / settled node*). As the normal node receives two beacons, it estimates two positions using

Bézout's theorem. According to Bézout's theorem *"The intersection of a variety of degree m with a variety of degree n in complex projective space is either a common component or it has mn points when the intersection points are counted with the appropriate multiplicity."* Position estimation of a node using Bézout's theorem is explained below.

Let (x, y) be the position of an unknown node and (a_1, b_1), (a_2, b_2) be the position of two of its neighbouring anchor nodes. Also, let the distance between an unknown node and the respective anchor nodes be d_1 and d_2 respectively. Then,

$$(x - a_1)^2 + (y - b_1)^2 = {d_1}^2 \tag{5.1}$$

$$(x - a_2)^2 + (y - b_2)^2 = {d_2}^2 \tag{5.2}$$

On re-arranging (5.1) and (5.2),

$$x^2 + y^2 = {d_1}^2 - {a_1}^2 - {b_1}^2 + 2a_1x + 2b_1y \tag{5.3}$$

$$x^2 + y^2 = {d_2}^2 - {a_2}^2 - {b_2}^2 + 2a_2x + 2b_2y \tag{5.4}$$

On comparing, (5.3) and (5.4), we have

$${d_1}^2 - {a_1}^2 - {b_1}^2 + 2a_1x + 2b_1y = {d_2}^2 - {a_2}^2 - {b_2}^2 + 2a_2x + 2b_2y \tag{5.5}$$

$$2(a_1 - a_2)x = ({d_2}^2 - {a_2}^2 - {b_2}^2 - {d_1}^2 + {a_1}^2 + {b_1}^2) + 2(b_2 - b_1)y \tag{5.6}$$

Let $z_0 = {d_2}^2 - {a_2}^2 - {b_2}^2 - {d_1}^2 + {a_1}^2 + {b_1}^2$

The eqation (5.6) can be reduced to

$$x = \frac{z_0 + 2(b_2 - b_1)y}{2(a_1 - a_2)} \tag{5.7}$$

For simplification, this can be written as

$$x = z + py \tag{5.8}$$

where $z = \dfrac{z_0}{2(a_1 - a_2)}$, and $p = \dfrac{2(b_2 - b_1)}{2(a_1 - a_2)}$

On substituting the value of x in equation (5.1), we obtained

$$(p^2 + 1)y^2 + (2zp - 2a_1p - 2b_1)y - ({d_1}^2 - {a_1}^2 - {b_1}^2 - z^2 + 2a_1z) = 0 \tag{5.9}$$

Solving the quadratic equation (5.9), we obtain y_1 and y_2. Let x_1 and x_2 be the values corresponding to y_1 and y_2 respectively. Therefore, the proposed algorithm estimates two positions $P_1(x_1, y_1)$ and $P_2(x_2, y_2)$.

In order to select the correct estimated position a *dead reckoning* approach is used. In this approach, a localized node say k uses its location p_{prev} at the checkpoint t_i to estimate its location in the next checkpoint at t_{i+1}. Let v be the velocity and t be the time duration between the two successive checkpoints. Then, the distance d traveled by the node k between two successive checkpoints is calculated as $d = v * t$. Therefore, at the checkpoint t_{i+1}, an unknown node knows its position at checkpoint t_i and the distance d traveled between the two successive checkpoints. Also, the node has two anchor positions, i.e., (a_1, b_1), (a_2, b_2). Node uses trilateration to calculate the position $P(\hat{x}, \hat{y})$. Then the node computes the correction factor *Cf* to select one of the two estimated positions P_1 and P_2. The correctness factor is computed as:

$$Cf_1 = \sqrt{(\hat{x} - x_1)^2 + (\hat{y} - y_1)^2}$$
$$Cf_2 = \sqrt{(\hat{x} - x_2)^2 + (\hat{y} - y_2)^2}$$

where Cf_1, Cf_2 represents the distance of position P_1, and P_2 from the position P estimated *via* trilateration. The correct position of the node is $P_1(x_1, y_1)$ if $Cf_1 < Cf_2$ else the correct position is $P_2(x_2, y_2)$. This is because, calculated position $P(\hat{x}, \hat{y})$ always deviates from the actual position by a small margin. Once a node is localized, it broadcasts a beacon. This process continues until the end of the checkpoint.

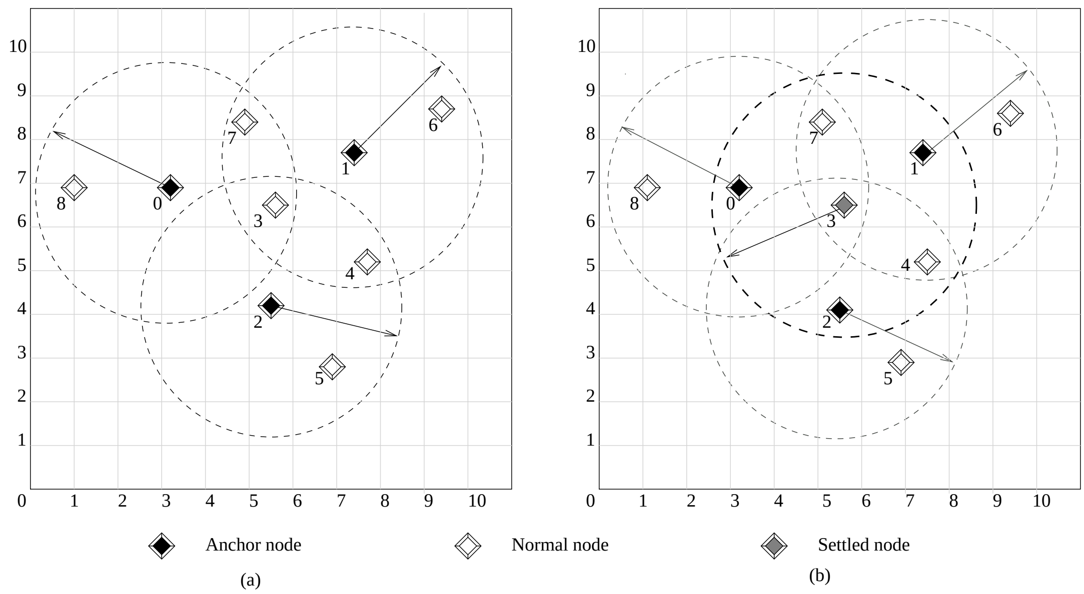


Figure 5.1: Initialization phase: (a) At the first checkpoint, anchor nodes transmit beacons and normal nodes localize via trilateration; (b) normal nodes that are short of 1 or 2 beacons localize with the help of settled nodes.

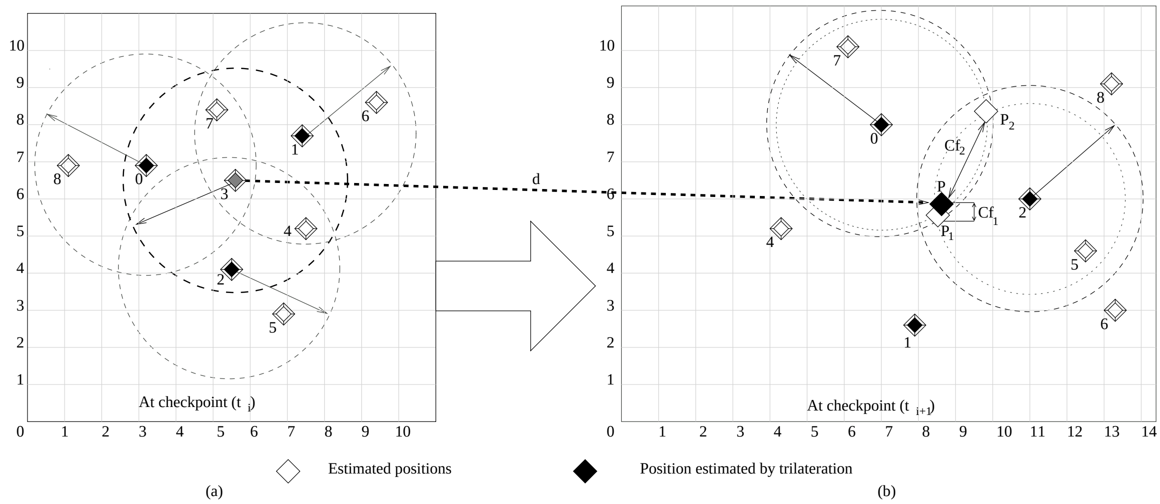


Figure 5.2: Normal node 3 at checkpoint t_{i+1} estimate two locations P_1 and P_2 using two anchor nodes 0 and 2. The correct position is selected by using the previous position of node 3 at checkpoint t_i.

We illustrate the localization in proposed scheme using Figure 5.1. Localization in the initialization phase is shown in Figure 5.1(a) and 5.1(b). Node 3 in Figure 5.1(a) receives beacon from three anchor nodes $0, 1$, and 2 at checkpoint t_i and localizes. Nodes 4 and 7 receives only two beacon, whereas nodes 5, 6, and 8 receives only one beacon. These nodes at this point of checkpoint t_i can not localize, as the number of beacons required for localization for the first time is *three*. Node 3 broadcast a beacon after localization. Nodes 4 and 7 gets localized after receiving beacon from node 3. This is shown in Figure 5.1(b). This co-operative, distributive process of localization continues until the end of the checkpoint. At the end of the checkpoint t_i, nodes 6 and 8 have only one beacon. Both these nodes delete the beacons and continue moving.

Figure 5.2(b) illustrate the sequent phase at checkpoint t_{i+1}. We consider node 3, to explain localization using two anchor nodes. Let the co-ordinate of node 3 at checkpoint t_i be $(5.5, 6.3)$ as shown in Figure 5.2(a), and the distance traveled during the checkpoint interval t_i and t_{i+1} be 3.5 unit. At checkpoint t_{i+1}, node 3 can be localized using two anchor nodes 0 and 2, this is shown in Figure 5.2(b). Let the co-ordinate of node 0 and 2 be $(7, 8)$ and $(11, 6)$ respectively as shown in Figure 5.2(b). Using Bézout's theorem node 3 estimate two locations $P_1(8.54, 5.54)$ and $P_2(9.98, 8.24)$. To select one of the above two locations dead reckoning approach is used. Based on the location of node 0, node 2 and its previous location, node 3 estimates its new location $P(\hat{x}, \hat{y})$ equal to $(8.78, 6.03)$ using trilateration technique. Then node 3 calculates the correctness factor Cf_1 and Cf_2 to find the least deviated estimated position from $P(\hat{x}, \hat{y})$. The computed value of Cf_1 and Cf_2 is 0.738 and 2.514 respectively. Since $Cf_1 < Cf_2$ the position $P_1(8.54, 5.54)$ is selected as the correct estimated position. It can be observed from the Figure 5.2(b) the actual position of node 3 is very close to the estimated position.

The proposed localization algorithm is given as Algorithm 1.

Algorithm 2: DRLMSN LOCALIZATION ALGORITHM

1 **Notation:** $\mathcal{A}$: Anchor node, $\mathcal{U}$: Unknown node, $\mathcal{S}$: Settled node
2 $beaconSet \leftarrow \phi$ /* Set of received locations. */
2 $locfirst \leftarrow 0$ /* Set to 1, if node has completed initialization phase. */
3 $P_{prev} \leftarrow -1$ /* Stores current position of a node for next checkpoint. */
4 $Status$ /* Indicates node type: Its value can be $\mathcal{A}$ or $\mathcal{U}$ or $\mathcal{S}$ */

For Anchor Node:

5 **if** $Status = \mathcal{A}$ **then**
6   broadcast *beacon*
7   start *waitTimer_1*

Event:

8 *waitTimer_1* timeout

Action:

9 broadcast *beacon*
10 restart *waitTimer_1* /* results in recursive broadcast of beacon. */

For Unknown/Settled Node:

Event:

11 received *beacon*

Action:

12 **if** $Status = \mathcal{U}$ **then**
13   start *waitTimer_2* /* Start of checkpoint. */
14     $beaconSet \leftarrow beaconSet \cup \{beacon\}$
15   **if** $(sizeof(beaconSet) \geq 3)$ *and* $(locfirst = 0)$ **then** /* Initialization phase. */
16         $Position \leftarrow Trilateration(beaconSet)$
17   broadcast *beacon*
18         $P_{prev} \leftarrow Position$
19         $locfirst \leftarrow 1$
20         $Status \leftarrow \mathcal{S}$
21   **else if** $(sizeof(beaconSet) \geq 2)$ *and* $(locfirst = 1)$ **then** /* Sequent phase. */
22         $Position \leftarrow$ Use $beaconSet$ and P_{prev}
23   broadcast *beacon*
24         $P_{prev} \leftarrow Position$
25         $Status \leftarrow \mathcal{S}$

else

26   delete *beacon* /* $\mathcal{A}$ or $\mathcal{S}$ do not need beacon. */

Event:

27 *waitTimer_2* timeout /* End of checkpoint. */

Action:

28 $beaconSet \leftarrow \phi$ /* Delete received beacons. */
29 $Status \leftarrow \mathcal{U}$ /* For localizing in next checkpoint settled node changes status to $\mathcal{U}$. */

Description of Algorithm 2: *In each checkpoint, anchor nodes broadcast beacons. This is mentioned in lines 5 – 10 of algorithm 2. Line 15 – 20 localizes a node in the initialization phase. In this phase a node needs three beacons for localization. Sequent phase* *localization is mentioned in lines 21 – 25. In this phase a node require only two beacon node for localization. Timer 1 causes anchor nodes to broadcast beacon at the start of each checkpoint recursively. Timer 2 controls duration of each checkpoint.*

5.4 Performance Evaluation

We have simulated the proposed scheme using Castalia simulator [46] that runs on the top of OMNET++. We made the following assumptions in our simulation: *(i)* nodes are considered to be homogeneous, with respect to transceiver power and receiver sensitivity. This helps in controlling the connectivity between nodes in the network easily; *(ii)* for simplicity, we consider transmission range of all the nodes as a perfect circle. This ensures that beacon packets transmitted by a neighbouring node are always received successfully; *(iii)* all sensor nodes are synchronized.

The key metric used for evaluating the localization algorithm is the accuracy in location estimation. We calculated the estimated error as the difference between the estimated position and the actual position. The average root mean square error (RMSE) is calculated as:

$$Average\ RMSE = \frac{\sum_{i=1}^{N-P} ||\hat{\theta}_i - \theta_i||}{N-P}$$

where $\hat{\theta}_i$ is estimated position, θ_i is actual position, N is the total number of nodes in the network, and P is number of anchor nodes.

We consider the following parameters in our simulation: (i) nodes are randomly deployed in a sensor field of area $200 \times 200\ m^2$; (ii) symmetric communication and the communication range is 20 meters; (iii) anchor node density is 10%. We define the anchor density as the ratio between the anchor nodes to the total nodes in the network; (iv) transmission power is -5 dBm; (v) path loss exponent (η) is 2.4; (vi) modified random waypoint mobility model [65] and random direction mobility model [66] are used. We compared DBNLE with another range based scheme called as RSS-MLE [63]. Through simulation, we studied the impact of mobility model, anchor density, node speed, number of normal nodes, and deployment topology on location estimation. Each of these is explained below.

Impact of Mobility Model: Mobility pattern plays an important role in the localization process. Besides increasing the network connectivity and coverage area, mobility affects the accuracy of localization and also drains the battery quickly. Mobility pattern of nodes affect both the localization accuracy and the percentage of localized nodes. We considered

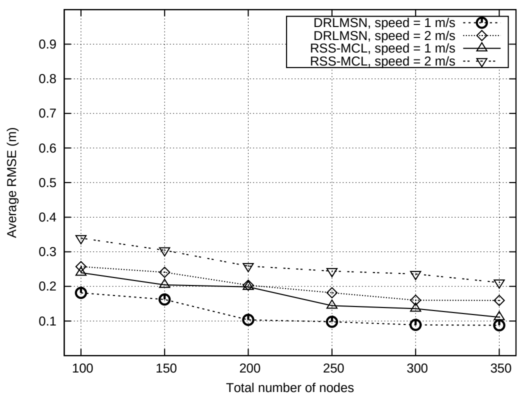


Figure 5.3: Impact of increase in the number of nodes on the localization error in modified random waypoint mobility model.

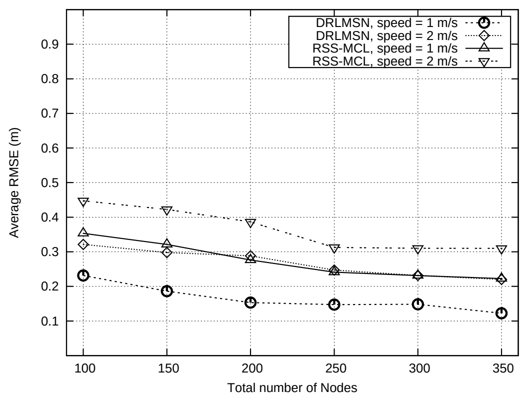


Figure 5.4: Impact of increase in the number of nodes on the localization error in random direction mobility model.

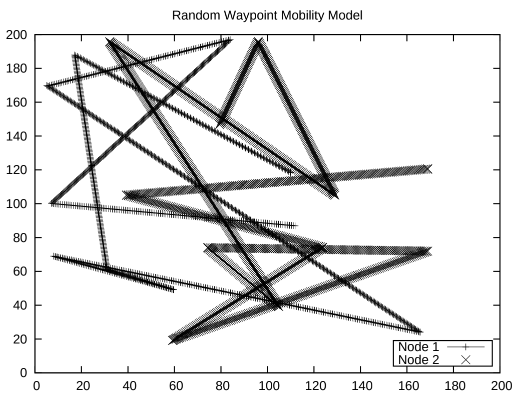


Figure 5.5: Mobility pattern of nodes in random waypoint mobility model.

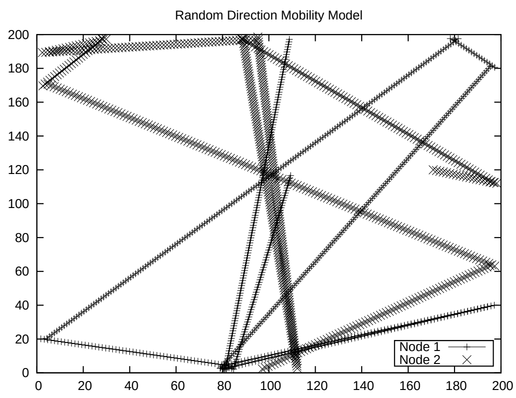


Figure 5.6: Mobility pattern of nodes in random direction mobility model.

two mobility models (i) Random Waypoint Mobility Model (RWMM), (ii) Random Direction Mobility Model (RDMM) and have shown the affect of mobility model on localization accuracy.

In RWMM, a node randomly chooses a new destination in a direction between $[0, 2\pi]$ and moves towards that destination with a speed in the range $[v_{min}, v_{max}]$. While in RDMM, a node randomly chooses a direction between $[0, 2\pi]$, a speed in the range $[v_{min}, v_{max}]$ and moves in the chosen direction upto the boundary of the network. After reaching the boundary same process is repeated. In both RWMM and RDMM, a node pauses for some predefined time before changing its direction. We have set the pausetime to be zero, in order to simulate a continuous mobility model. From Figure 5.3 it is observed that RWMM has

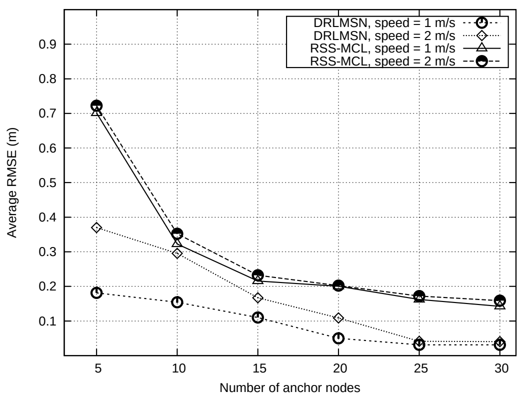


Figure 5.7: Impact of increase in anchors on the localization error in modified random waypoint mobility model.

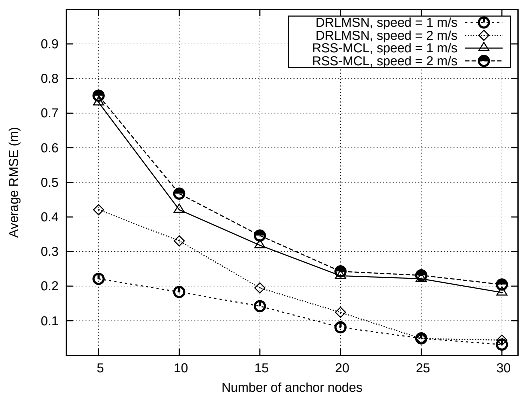


Figure 5.8: Impact of increase in anchors on the localization error in random direction mobility model.

less average RMSE than RDMM as shown in Figure 5.4. The reason for this difference in error is due to mobility pattern of nodes. In RWMM, nodes mostly move within the vicinity of the center. They are less likely to move towards the boundaries of the network as shown in Figure 5.5. Therefore, a node will have relatively higher number of neighbours. As a result, a normal node selects the most nearest neighbours which results in less inaccuracy. In contrast to this, in RDMM a node moves uniformly throughout the field as shown in Figure 5.6. This type of movement does not favors the selection of best neighbours, because a node is surrounded by lesser number of neighbours. It is observed that average RMSE is less in DBNLE as compared to RSS-MCL from Figure 5.3 and 5.4 . RSS-MCL uses more number of beacons for filtration of generated samples as compared to DBNLE which uses only 2–3 beacons. But due to mobility, increasing dependency on the number of beacons used increases uncertainty in position estimation. Among the two mobility models, RDMM increases network the coverage while as RWMM increases the connectivity among nodes.

Impact of anchor nodes: Keeping the network size fixed, increase in the anchor density results in the localization of more nodes in less time. This is because, most of the nodes get good number of anchor neighbour nodes. To find the effect of anchor density on localization error we varied the anchor density between 5% to 20% keeping the total number of nodes fixed at 200. The plot for anchor density *vs.* localization error in RWMM and RDMM is shown in Figure 5.7 and 5.8 respectively. It is observed from the figures that the average RMSE decreases with the increase in the anchor density. This is because: (*i*) higher the anchor density, lesser the number of nodes to be localized; (*ii*) a node gets more number of accurate beacons - resulting in lesser error accumulation and propagation. It is also observed with an increase in anchor density the average rate of decrease of RMSE is higher, and at a higher anchor density the rate of decrease is lesser. Increase in the number of anchors do not affect average RMSE to a greater extent in RSS-MCL as compared to DBNLE. This is because in RSS-MCL position estimation depends heavily on the quality of sample generation where as in DBNLE it directly depends on the number of beacons received. Furthermore, average RMSE is less in RWMM as compared RWDM. This is attributed to the neighbor density. In RWMM, a node has higher neighbour density as compared to RDMM.

Impact of node speed: The effect of speed on the average RMSE by varying anchor and node density is shown in Figure 5.3, 5.4, 5.7, and 5.8. It is observed from the above figures that with the increase in speed the localization error also increases. The above figures shows that the location estimation of a node in mobile WSNs is greatly affected by the node speed. With the increase in speed, a node covers more distance per unit time. This increase in speed results in: *(i)* increase in the uncertainty of localizing a node accurately, as the area over which a node needs to be localized increases, *(ii)* with the increase in distance covered, multi-path fading and shadowing comes into play. This affects the distance measurements and decreases the efficiency of range based localization algorithm, *(iii)* it also affects the basic functionality, *i.e.*, sensing is not properly done when a node moves too fast, *(iv)* it increases the localization percentage in low anchor density networks because increase in speed increases the network coverage.

Impact of normal nodes: The plot for normal nodes *vs.* localization error is shown in Figure 5.3 and 5.4 respectively. Total number of nodes taken are between 100 and 350 in order to find the impact of localization process in large networks. With increase in the number of normal nodes there is a significant increase in the percentage of localized nodes. This also results in the decrease of localization time and error. Decrease in localization time is attributed to more number of localized neighbours of a normal node. It is observed from the Figure 5.3 and 5.4 that localization error decreases gradually with the increase of nodes. The reason for this decrease is the selection of more number of nearest in-range neighbours. Closer is the neighbour lesser is the ranging error; as the quality of signal (RSSI) is directly affected by the distance between the transmitter and receiver node.

Impact of deployment/topology of nodes: Next, we consider the effect of deployment on localization error. We consider two deployment scenario: (*i*) random, and (*ii*) grid

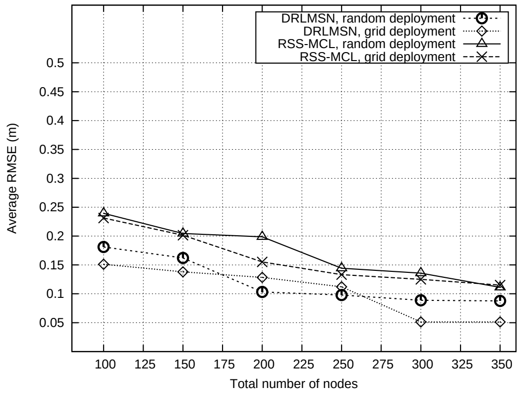


Figure 5.9: Impact of node deployment on the localization error in modified random waypoint mobility model.

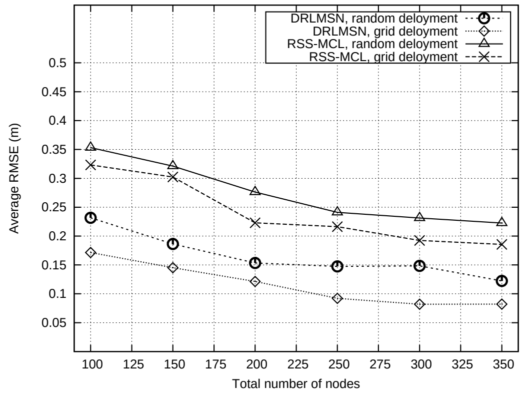


Figure 5.10: Impact of node deployment on the localization error in random direction mobility model.

to study the effect on localization error. In some cases nodes did not localize early and take time to localize. Consequently, this increases the localization time of whole network. This is because, nodes did not receive requisite number of beacons for localization. One of the major cause found for this is the way in which nodes are deployed initially and the manner in which nodes move. It is observed that if nodes are randomly deployed, then 30% of the nodes fail to localize in the first 2 to 3 checkpoints, whereas in grid network around 90% of nodes localize in the first checkpoint itself. In the next checkpoint all nodes get localized. From the Figure 5.9 and 5.10, it is observed that the localization error is lesser in grid deployment than in random deployment.

Finally, we studied the percentage of nodes localized at different checkpoints. The plot for percentage of localized nodes *vs.* checkpoints is shown in Figure 5.11 and 5.12. It is observed that the percentage of nodes localized increases as the checkpoint increases. Majority of the nodes gets localized after the 4^{th} checkpoint. Percentage of localized nodes in RSS-MCL is relatively less as compared in DRLMSN. Main reason responsible for this is the more time taken for sample generation and filtering than checkpoint duration. As a result most of the nodes fail to localize in RSS-MCL due to this time constraint.

5.5 Summary

A large number of localization techniques have been developed for static WSNs. These techniques can not be applied to mobile WSNs. Only a few localization techniques has

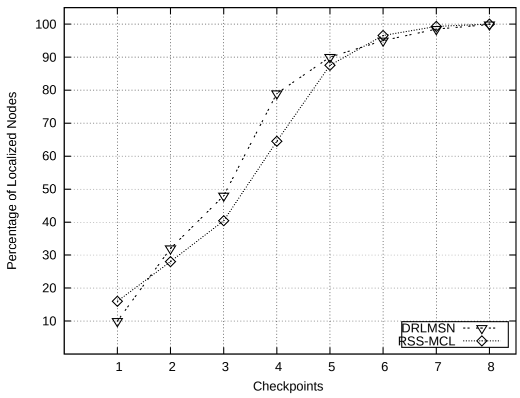


Figure 5.11: Percenatge of localized nodes at successive checkpoints in modified random waypoint mobility model.

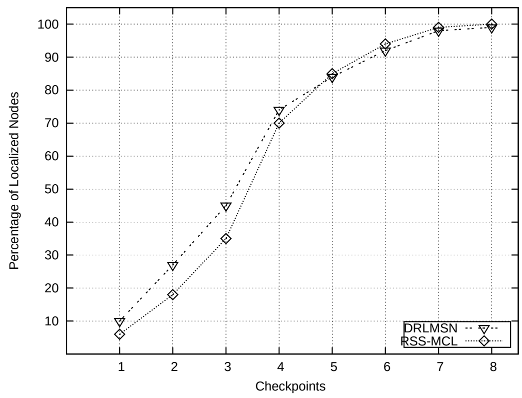


Figure 5.12: Percenatge of localized nodes at successive checkpoints in random direction mobility model.

been proposed for mobile WSNs. Most of these techniques considered either normal node or anchor nodes to be static. In this chapter we proposed a localization technique called dead reckoning for mobile WSN. We have considered both the normal nodes and anchor nodes to be mobile. As the nodes move in a sensor field, their position changes with time. Therefore, a mobile node has to be localized as long as it is alive. In the proposed technique, nodes are localized at discrete time intervals called checkpoint. A normal node is localized for the first time using three anchor nodes. For subsequent localization it uses only two anchor nodes and a technique called dead reckoning. Therefore, reducing the number of anchor nodes required from 3 to 2 at various checkpoints result in: (*i*) less localization time, and (*ii*) lesser localization error as compared to 3 anchor nodes, because more number of measurements incorporate more inaccurate readings due to multipath and shadowing effects. We have evaluated the localization error in the proposed scheme by varying the node density, anchor density, node speed, deployment type and mobility pattern.

In the next chapter, we summarize the contribution made in the thesis. We have also mentioned the possible future research areas in localization.

Chapter 6

Conclusions

Localization in wireless sensor networks have received increasing attention over the last one decade. It not only provides the geographical position of a sensor node but also fills the pre-requisite for geographic routing, spatial querying, and data dissemination. With the continuous research in localization of sensor networks, a number of effective algorithms have been proposed, but the stability has not yet reached. This is because of the meager resources (storage, battery, processor) and the harsh deployment environments. Currently, none of the localization techniques is able to full-fill all these constraints. Most existing localization algorithms for static WSNs were designed to work with at least three anchor nodes except in those cases where directional antenna is used. Usage of antenna not only increases the cost, but also the size of node as well as complexity of the algorithm. As the number of anchor nodes required in a network increases, overall cost of the network also increases. In addition, energy drainage of the network increases, but the localization time of the whole network decreases. Further, anchor nodes installed with GPS do not work well everywhere. Therefore, at present we are in the need of a novel technology that will solve the following problems: (*i*) reduce the number of required anchor nodes, (*ii*) localize sensor nodes in areas where GPS do not work well, (*iii*) minimize the localization error.

In this thesis we have proposed localization technique for static as well as mobile WSNs. In the reminder of this concluding chapter, we briefly summarize the original contributions of the study. Finally, some suggestions for future work are given.

6.1 Contribution

Localization Using a Single Anchor Node: First, we proposed a technique for localization, in a grid environment using a single anchor node. It is a distributed, range based technique. In this technique we classify the nodes into three types. They are: *(i)* anchor node, *(ii)* special node, and *(iii)* unknown node. Special nodes localize themselves with respect to anchor node. Unknown node localize with the help of anchor node and special node. We have compared the proposed scheme with a contemporary scheme called Multi-duolateration (MDL). We have observed that the localization time and localization error is smaller in the proposed scheme.

Distributed Binary Node Localization Estimation Approach: It is a distributed, range based localization algorithm for networks deployed in grid pattern. In this technique an unknown node is localized using two location aware nodes. This technique is compared with MDL. It is found that the localization time and localization error is less compared to MDL.

Dead Reckoning Localization Technique: This technique is proposed for mobile WSNs while the previous two techniques are for static WSNs. Mobile sensor nodes continuously change their positions. Therefore, each sensor node needs to be repetitively localized after certain time interval. This continuously localizing reduces the battery life of sensor nodes. Furthermore, it is too difficult to localize the mobile sensor nodes accurately as uncertainty increases with the mobility.

In this technique a node is localized using two anchor nodes. There are two phases in localization. They are: *(i) Initialization phase:* In this phase, a node localizes using trilateration mechanism. Until a node localizes itself using three anchor nodes, it remains in the initialization phase. *(ii) Sequent phase:* In this phase a node localizes itself using only two anchor nodes. Nodes are localized at discrete time interval called *checkpoints*. A *dead reckoning* approach is used to identify the correct estimated position. Once a node is localized in either of the two phases, it act as settled node and broadcasts a beacon during the checkpoint.

6.2 Direction for Future Research

Localization problem in WSNs is not yet fully solved. There are several issues in localization which need further attention. Some of these are below:

(*i*) Localization accuracy is mostly affected by the ranging techniques used. Each ranging technique in turn is severely affected by the wireless channel behaviour in different environments. Therefore, for accurate localization, issues like signal fading, multipath, additive noise etc needs to be addressed.

(*ii*) Error in distance measurement between nodes need to be handled with proper calibration because most of localization algorithms depend on the pair-wise distance.

(*iii*) Not enough work has been drawn on the localization of mobile WSNs. Owing to more battery drainage in mobile networks, a predictive approach for localization can estimate the node location with less number of anchors required.

(*iv*) Monte - Carlo localization (MCL) approach for mobile WSNs needs more attention to reduce the valid sample generation space. Time required for the generation of valid samples can be reduced by doing the generation and filtering of samples simultaneously.

(*v*) Localization technique for mobile WSNs needs to be tested in various mobility models. This ensures that each new proposed technique operate properly in real time networks.

(*vi*) Furthermore, localization of WSN in certain specific environments like under-water environments has not been explored much.

Bibliography

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. Wireless Sensor Networks: A Survey. *Computer Networks*, 38:393–422, 2002.

[2] P. Juang, H. Oki, Y. Wang, M. Martonosi, Li S. Peh, and D. Rubenstein. Energy-Efficient Computing for Wildlife Tracking: Design Tradeoffs and Early Experiences with Zebranet. In *Proceedings of the 10th International Conference on Architectural Support for Programming Languages and Operating Systems*, ASPLOS X, pages 96–107, New York, NY, USA, 2002. ACM.

[3] I. Stojmenovic. *Handbook of Sensor Networks : Algorithms and Architectures*, chapter 1: Introduction to Wireless Sensor Networking, pages 1–34. John Wiley and Sons, first edition, 2005.

[4] I. Mahgoub and M. Ilyas. *SMART DUST: Sensor Network Applications, Architecture, and Design*, chapter 1: Opportunities and Challenges in Wireless Sensor Networks, pages 1–13. Taylor and Francis, first edition, 2006.

[5] A. Pascale, M. Nicoli, F. Deflorio, B. Dalla Chiara, and U. Spagnolini. Wireless Sensor Networks for Traffic Management and Road Safety. *IET Intelligent Transport Systems*, 6(1):67–77, 2012.

[6] Dan Li, K. D. Wong, Yu Hen Hu, and A. M. Sayeed. Detection, Classification, and Tracking of Targets. *IEEE Signal Processing Magazine*, 19(2):17–29, 2002.

[7] J. G. Ko, C. Lu, M. B. Srivastava, J. A. Stankovic, A. Terzis, and M. Welsh. Wireless Sensor Networks for Healthcare. *Proceedings of the IEEE*, 98(11):1947–1960, 2010.

[8] K. Lorincz, D. J. Malan, T. R. F. Fulford-Jones, A. Nawoj, A. Clavel, V. Shnayder, G. Mainland, M. Welsh, and S. Moulton. Sensor Networks for Emergency Response: Challenges and Opportunities. *IEEE Pervasive Computing*, 3(4):16–23, 2004.

[9] L. Buttyán, D. Gessner, A. Hessler, and P. Langendoerfer. Application of Wireless Sensor Networks in Critical Infrastructure Protection: Challenges and Design Options. *IEEE Wireless Communications*, 17(5):44–49, 2010.

[10] J. Zheng and A. Jamalipour. *Wireless Sensor Networks A Networking Perspective*, chapter 13: Sensor Network Standards, pages 407–431. John Wiley and Sons, first edition, 2009.

[11] B. Krishnamachari. *Networking Wireless Sensors*, chapter 4: Time Synchronization, pages 57–68. Cambridge University, first edition, 2005.

[12] F. Koushanfar, M. Potkonjak, and A. Sangiovanni-Vincentell. Fault Tolerance Techniques for Wireless Ad hoc Sensor Networks. In *Proceedings of IEEE Sensors*, volume 2, pages 1491–1496, 2002.

[13] Y. Liu and Z. Yang. *Location, Localization, and Localizability*, chapter 7: Localization for Mobile Networks, pages 97–109. Springer, first edition, 2011.

[14] S. K. Das, J. Wang, R. K. Ghosh, and R. Reiger. *Theoretical Aspects of Distributed Computing in Sensor Networks*, chapter 9: Algorithmic Aspects of Sensor Localization, pages 257–259. Springer, first edition, 2011.

[15] L. Hu and D. Evans. Localization for Mobile Sensor Networks. In *Proceedings of the 10th annual International Conference on Mobile Computing and Networking*, MobiCom '04, pages 45–57, Philadelphia, PA, USA, 2004. ACM.

[16] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan. The Cricket Location-Support System. In *Proceedings of the 6th annual international conference on Mobile computing and networking*, MobiCom '00, pages 32–43, New York, NY, USA, 2000. ACM.

[17] A. Ward, A. Jones, and A. Hopper. A New Location Technique for The Active Office. *IEEE Personal Communications*, 4(5):42–47, 1997.

[18] N. B. Priyantha, Allen K. L. Miu, H. Balakrishnan, and S. Teller. The Cricket Compass for Context-Aware Mobile Applications. In *Proceedings of the 7th annual international conference on Mobile computing and networking*, MobiCom '01, pages 1–14, New York, NY, USA, 2001. ACM.

[19] J. Zheng, C. Wua, and Yang Xua Hao Chua. An Improved RSSI Measurement In Wireless Sensor Networks. *Procedia Engineering(Elsevier)*, 15:876–880, 2011.

[20] D. C. Jenn. Transmission Equation for Multiple Cooperative Transmitters and Collective Beamforming. *IEEE Antennas and Wireless Propagation Letters*, 7:606–608, 2008.

[21] C. Savarese, J. M. Rabaey, and K. Langendoen. Robust Positioning Algorithms for Distributed Ad-hoc Wireless Sensor Networks. In *Proceedings of the General Track of the annual conference on USENIX Annual Technical Conference*, ATEC '02, pages 317–327, Berkeley, CA, USA, 2002. USENIX Association.

[22] A. Boukerchie, Horacio A. B. F. Oliveria, E. F. Nakamura, and A. A. F. Loureiro. Localization Systems For Wireless Sensor Networks. *IEEE Wireless Communications*, 14(6):6–12, 2007.

[23] L. Kleinrock and J. Silvester. Optimum Transmission Radii for Packet Radio Networks or Why Six is a Magic Number. In *Proceedings of National Telecommunications Conference*, volume 1 of *NTC '78*, pages 4.3.1–4.3.5, 1978.

[24] R. Nagpal, H. Shrobe, and J. Bachrach. Organizing a Global Coordinate System from Local Information on an Ad hoc Sensor Network. In *Proceedings of the 2nd International Workshop on Information Processing in Sensor Networks*, ISPN 03, Palo Alto, California, April, 2003.

[25] I. Stojmenovic. *Handbook of Sensor Networks Algorithms and Architectures*, chapter 9: Localization in Sensor Networks, pages 277–310. John Wiley and Sons, first edition, 2005.

[26] I. F. Akyildiz and M. C. Vuran. *Wireless Sensor Networks*, chapter 12: Localization, pages 265–284. John Wiley and Sons Ltd, first edition, 2010.

[27] N. Bulusu, J. Heidemann, and D. Estrin. GPS-less Low-Cost Outdoor Localization for Very Small Devices. *IEEE Personal Communications*, 7(5):28–34, Oct. 2000.

[28] X. Li, H. Shi, and Y. Shang. A Partial-Range-Aware Localization Algorithm for Ad-hoc Wireless Sensor Networks. In *Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks*, LCN '04, pages 77–83, 16–18 Nov. 2004.

[29] Y. Wang, X. Wang, D. Wang, and D. P. Agrawal. Range-Free Localization Using Expected Hop Progress In Wireless Sensor Networks. *IEEE Transactions on Parallel and Distributed Systems*, 20(10):1540–1552, Oct. 2009.

[30] T. He, C. Huang, B. Blum, J. Stankovic, and T. Abdelzaher. Range Free Localization Schemes in Large Scale Sensor Networks. In *Proceedings of the 9th annual International Conference on Mobile Computing and Networking*, MobiCom '03, pages 81–95, 14–19 Sep. 2003.

[31] S. Simic and S. S. Sastry. Distributed Localization in Wireless Ad-hoc Networks. Technical Report UCB/ERL M02/26, EECS Department, University of California, Berkeley, 2002.

[32] C. Whitehouse. The Design of Calamari: An Ad-hoc Localization System for Sensor Networks. Technical report, Master's thesis, University of California, Berkeley, 2002.

[33] J.-P. Sheu, J.-M. Li, and C.-S. Hsu. A Distributed Location Estimating Algorithm for Wireless Sensor Networks. In *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing*, volume 1 of *SUTC '06*, pages 218–225, 5–7 June 2006.

[34] J.-P. Sheu, P.-C. Chen, and C.-S. Hsu. A Distributed Localization Scheme for Wireless Sensor Networks with Improved Grid-Scan and Vector-Based Refinement. *IEEE Transactions on Mobile Computing*, 7(9):1110–1123, 2008.

[35] Y. Shang, W. Ruml, Y. Zhang, and M. P. J. Fromherz. Localization From Mere Connectivity. In *Proceedings of the 4th ACM international symposium on Mobile Ad-hoc networking and computing*, (MobiHoc '03), pages 201–212, New York, NY, USA, 1–3 June 2003. ACM.

[36] F. K. W. Chan and H. C. So. Efficient Weighted Multidimensional Scaling For Wireless Sensor Network Localization. *IEEE Transactions on Signal Processing*, 57(11):4548–4553, 2009.

[37] S. Zhu and Z. Ding. Bridging Gap Between Multi-dimensional Scaling Based and Optimum Network Localisation via Efficient Refinement. *IET Signal Processing*, 6(2):132–142, 2012.

[38] V. Chandrasekhar and W. Seah. An Area Localization Scheme for Underwater Sensor Networks. In *OCEANS '06*, pages 1–8, 16–19 May 2007.

[39] H. M. Khan, S. Olariu, and M. Eltoweissy. Efficient Single-Anchor Localization In Sensor Networks. In *Proceedings Of The Second IEEE Workshop On Dependability and Security in Sensor Networks and Systems*, DSSNS '06, pages 35–43, 24–28 April 2006.

[40] D. Kumar and S. Varma. An Efficient Localization Based On Directional Antenna For Wireless Sensor Networks (WSNs). *International Journal of Computer and Electrical Engineering*, 1(5):542–549, Dec. 2009.

[41] B. Zhang and F. Yu. LSWD: Localization Scheme For Wireless Sensor Networks Using Directional Antenna. *IEEE Transactions on Consumer Electronics*, 56(4):2208–2216, Nov. 2010.

[42] U. A. Khan, S. Kar, and J. M. F. Moura. Distributed Sensor Localization In Random Environments Using Minimal Number Of Anchor Nodes. *IEEE Transactions on Signal Processings*, 57(5):2000–2016, May 2009.

[43] H. Lee, Y. Kim, and H. Chong. Grouping Multi-Duolateration Localization Using Partial Space Information For Indoor Wireless Sensor Networks. *IEEE Transactions on Consumer Electronics*, 55(4):1950–1958, 2009.

[44] A. Abramo, F. Blanchini, L. Geretti, and C. Savorgnan. A Mixed Convex/nonconvex Distributed Localization Approach for the Deployment of Indoor Positioning Services. *IEEE Transactions on Mobile Computing*, 7(11):1325–1337, 2008.

[45] S. Zhu and Z. Ding. Distributed Cooperative Localization of Wireless Sensor Networks with Convex Hull Constraint. *IEEE Transactions on Wireless Communications*, 10(7):2150–2161, 2011.

[46] A. Boulis. Castalia: A simulator for Wireless Sensor Networks and Body Area Networks. NICTA: National ICT Australia, March 2011.

[47] A. Galstyan, B. Krishnamachari, K. Lerman, and S. Pattem. Distributed Online Localization in Sensor Networks Using a Moving Target. In *Third International Symposium on Information Processing in Sensor Networks (IPSN)*, ISPN 04, pages 61–70, 26–27 April 2004.

[48] P. N Pathirana, N. Bulusu, A. V Savkin, and S. Jha. Node Localization Using Mobile Robots in Delay-Tolerant Sensor Networks. *IEEE transactions on Mobile Computing*, 4(3):285–296, May-June 2005.

[49] K.-F. Ssu, C.-H. Ou, and H. C. Jiau. Localization with Mobile Anchor Points in Wireless Sensor Networks. *IEEE transactions on Vehicular Technology*, 54(3):1187–1197, May 2005.

[50] J. Jiang, G. Han, H. Xu, Lei Shu, and M. Guizani. LMAT: Localization with a Mobile Anchor Node Based on Trilateration in Wireless Sensor Networks. In *Global Telecommunications Conference*, GLOBECOM '11, pages 1–6, 5–9 Dec. 2011.

[51] P. Bergamo and G. Mazzimi. Localization in Sensor Networks with Fading and Mobility. In *The 13th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, volume 2, pages 750–754, 15–18 Sept. 2002.

[52] L. L. de Oliveira, João B. Martins, G. Dessbesell, and José Monteiro. CentroidM: A Centroid-based Localization Algorithm for Mobile Sensor Networks. In *Proceedings of the 23rd Symposium on Integrated Circuits and System Design*, SBCCI '10, pages 204–209, New York, NY, USA, 2010. ACM.

[53] J.-P. Sheu, W.-K. Hu, and J.-C. Lin. Distributed Localization Scheme for Mobile Sensor Networks. *IEEE Transactions on Mobile Computing*, 9(4):516–526, 2010.

[54] Z. Wang, Y. Wang, M. Ma, and J. Wu. Efficient Localization for Mobile Sensor Networks Based on Constraint Rules Optimized Monte Carlo Method. *Computer Networks*, 57(14):2788 – 2801, 2013.

[55] H. J. Rad, A. Amar, and G. Leus. Cooperative Mobile Network Localization via Subspace Tracking. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, ICASSP '11, pages 2612–2615, 2011.

[56] V. Savic and S. Zazo. Cooperative Localization in Mobile Networks using Nonparametric Variants of Belief Propagation. *Ad Hoc Networks*, 11(1):138 – 150, 2013.

[57] M. Nicoli, S. Gezici, Z. Sahinoglu, and H. Wymeersch. Localization in Mobile Wireless and Sensor Networks. *EURASIP Journal on Wireless Communications and Networking*, 2011(1):1–3, 2011.

[58] H. Chen, F. Gao, M. Martins, P. Huang, and J. Liang. Accurate and Efficient Node Localization for Mobile Sensor Networks. *Mobile Networks and Applications*, 18(1):141–147, 2013.

[59] S. Tilak, V. Kolar, N. B. Abu-Ghazaleh, and K. D. Kang. Dynamic Localization Control for Mobile Sensor Networks. In *24th IEEE International Conference on Performance, Computing, and Communications*, IPCC '05, pages 587–592, 7–9 April 2005.

[60] A. Baggio and K. Langendoen. Monte Carlo Localization for Mobile Wireless Sensor Networks. *Ad Hoc Networks*, 6(5):718–733, july 2008.

[61] M. Rudafshani and S. Datta. Localization in Wireless Sensor Networks. In *Proceedings of the 6th International Conference on Information Processing in Sensor Networks*, ISPN '07, pages 51–60, Cambridge, Massachusetts, USA, 2007. ACM.

[62] Z. Shigeng, J. Cao, C. Lijun, and C. Daoxu. Locating Nodes in Mobile Sensor Networks More Accurately and Faster. In *5th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks*, SECON '08, pages 37–45, 16–20 June 2008.

[63] W. D. Wang and Q. X. Zhu. RSS-Based Monte Carlo Localisation for Mobile Sensor Networks. *IET Communications*, 2(5):673–681, 2008.

[64] R. R. Roy. Reference Point Group Mobility. In *Handbook of Mobile Ad Hoc Networks for Mobility Models*, pages 637–670. Springer US, 2011.

[65] C. Schindelhauer. Mobility in Wireless Networks. In *Proceedings of the 32nd Annual Conference on Current Trends in Theory and Practice of Computer Science*, SOFSEM '06, pages 100–116, Berlin, Heidelberg, 2006. Springer-Verlag.

[66] E. M. Royer, P. Michael Melliar-Smithy, and L. E. Moser. An Analysis of the Optimum Node Density for Ad hoc Mobile Networks. In *IEEE International conference on Communications, ICC*, volume 3, pages 857–861, 2001.