INDOOR LOCALIZATION SCHEMES FOR MOBILE ROBOTS

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Indoor Localization Schemes for Mobile Robots

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ABSTRACT

Mobile robots have taken a major role in indoor environments where they are used to accomplish high risk tasks instead of human beings, for example in war circumstances, dangerous chemical interactions, etc. Localization of a mobile robot is the problem of determining the location of the robot as it navigates within an environment. Localization of mobile robots outdoors is mainly done based on GPS (Global Positioning System). GPS consists of several satellites orbiting the earth and broadcast data to indicate location and current time. The distance is determined by the time for the signals to reach the receiver from at least four satellites. The GPS system works well for outdoor terminals but cannot be used indoors because it needs a line-of sight between the satellites and the receiver. Other localization techniques based on sensors like sonar, infrared, cameras, etc. are used for indoor localization, but these sensors need intensive processing to get accurate readings, in addition to other limitations such as sonar's beams collision, cost, cameras resolution and image processing time delays.

In this research, a different technique based on Wireless Sensor Networks (WSN) has been investigated for mobile robot localization. In particular, we investigate four scenarios for the target localization which are localization using static motes only, dynamic motes only, cooperative hybrid model and hybrid model. The proposed system utilizes a combination of static and mobile sensor nodes to collaborate in localizing and capturing a target using wireless

transmission. Static nodes guide mobile nodes into localizing the target using some of the special characteristics of the target like signal strength, frequency, sound, temperature, etc. Each mobile node will gather information about the target and execute an algorithm to set its trajectory towards the target. Each mobile node will share its knowledge with others to improve their localization decision.

The implemented system has several features. First, it achieves good accuracy because of the involvement of many nodes in the estimation process and the communication between mobile and static motes to localize the target. Second, it is robust to node failure since if one of the nodes is not working the rest of motes can collaborate to compensate for the missing data and localize the target accurately.

Simulation results of localization based on static, dynamic, hybrid, and co-hybrid models are presented in this report. Comparison of the results of the various simulated models is based on Mean Square Error MSE of the localization and received Signal-to-Noise ratio (SNR). It is shown that localization using static motes outperformed other models. Using the same criteria, the Hybrid & Co Hybrid localization models were next in performance. Target localization based on dynamic motes gave the worst performance. The effect of wireless channel shadowing on the performance of the proposed schemes is also presented.

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To my parents and husband,

for your endless love, care, and unwavering faith in me

Chapter 1 INTRODUCTION

1.1 OVERVIEW

Nowadays, robots applications have increased rapidly not only in using static robots, where they gather and process data, but also in the use of mobile robots to navigate within an environment and do more complicated tasks. As mobile robots need to navigate, they need to know and learn about their environment which leads to the term of localization.

Localization of mobile robots could be done indoors or outdoors where they use different localization methods. For outdoor localization Global Positioning System (GPS) are mostly used where communication with satellite is needed to provide reliable location. On the other hand sensors, and any data acquisition devices, are used to estimate the location indoors since the GPS is not a possible solution. The challenge in localizing mobile robots is there mobile trajectory or behavior. Localization of mobile robots has been spread to do perform risky tasks such as monitoring in hazardous environments and industrial applications.

Wireless Sensor Networks (WSN) are used for indoor and outdoor localization, where a set of sensors are used to gather data about the environment. Sensors such as temperature, pressure, audio, etc. are packed in one device along with a processor, and a wireless module in order to communicate and process data collected from the environment. WSNs are employed in various applications such as military, medical and industrial applications.

Sensor networks are the key technology to gathering the information needed to achieve smart environments. Smart environment is a timely development with important applications for both civil and military applications. Important civil applications include habitat monitoring, smart buildings, intelligent utilities, precision agriculture, smart industrial environment, smart homes, shipboard, intelligent transportation systems [1-2], and many other application. Military applications were among the first of this technology [3] such as recent terrorist and revolutionary warfare countermeasures that require distributed networks of sensors that can be deployed based on military application requirement. In such applications, running wires or cabling is impractical and therefore a wireless sensor network is typically needed. Other features that promote the use of WSN are fast and easy deployment and robustness to faults [4].

The proposed research topic is motivated by the recent introduction of wireless sensor network applications development in the mechatronics center at the American University of Sharjah. There are several projects introduced in the mechatronics center that could benefit significantly from the use of mobile ad hoc wireless sensor networks (MASNet) such as the robot soccer project, the multi-agent cooperative strategies for mobile robots, and the autonomous unmanned systems research activities. The use of smart technologies by the oil and gas sectors in the region is another important industrial application where the current research would be useful.

Motivated by the enabling capabilities of MASNet, an application scenario was created by integrating static and dynamic motes into a hybrid system of mobile ad hoc wireless sensor network to simulate the capturing of a target utilizing hybrid of WSN and set of mobile robots carrying similar sensor platforms. The objective is for the mobile robots to localize themselves and achieve their goal using information sent by the available static nodes.

1.2 BACKGROUND

1.2.1 LOCALIZATION

Localization of a network device leads to the meaning of positioning, where each node in the network environment needs to know its own location to be able to perform the tasks assigned to it. This process needs computational methods in order to find the distance between different nodes which is called relative distance and further computations could be done to find the coordinates accordingly.

Localization could be classified as indoor localization and outdoor localization, where each has it is own methods for positioning. For example, military applications, and animal vocalization are mostly outdoor applications that use global positioning system (GPS) to locate sensor nodes in a WSN [5]. As GPS poorly operates for indoor applications, other localization techniques are used for indoors such as Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AOA) [6].

Monocular and straight line correspondences are used for incremental model based localization for an indoor mobile robot, [7].Other examples of indoor localization techniques are based on the use of ultrasonic sensor localization system for mobile robot localization [8] [9]. Camera based localization for indoor application was used for mobile robot localization in [10].

An Indoor localization study has been presented in [11], where two methods were investigated in case of the initial position to be unknown. The first method is based on multiple hypothesis tracking and the second is an experimentally verified improvement of the Monte Carlo Localization technique.

A technique based on using spinning beacons for precise indoor localization was discussed in [12], where beacons are used to create and detect predictable and highly distinguishable Doppler signals for sub-meter localization accuracy. Multiple wireless technologies were used for indoor localization in [13] such as location fingerprints, interpolation points and anchors.

Wireless Sensor Networks (WSNs) provide a new paradigm for sensing and disseminating information from various environments, with the potential to serve many and diverse applications. A WSN consists of a number of sensors spread over an area with signal processing, wireless communication and networking capabilities [1]. Sensors integrated into structures, machinery, and the environment, coupled with the efficient delivery of sensed information, could provide tremendous benefits to society. Potential benefits include: fewer catastrophic failures, conservation of natural resources, improved manufacturing productivity, improved emergency response, and enhanced homeland security [14][15][16][17].

The use of WSN in localization applications has been considered by different researches. For example, a mobile-assisted localization method which employs a mobile user to assist in measuring distances between node pairs until these distance constraints form a "globally rigid" structure that guarantees a unique localization was introduced in [18]. A gradient driven method [19], called GraDrive, is used to predict the position of a stationary target in a WSN. The method integrates per-node prediction with global collaborative prediction to estimate the position of a stationary target and direct the mobile nodes toward the target without prior map. A system of wireless sensor network with limited infrastructural support used to improve the energy efficiency of a wireless sensor network in [20], where wires are used as shortcuts to reduce the average hop-count of the network. The sequential Monte Carlo Localization method was introduced in [21], where it can exploit mobility to improve the accuracy and precision of localization in WSN.

MASnet (Mobile Actuator Sensor Network) is a project that adds node mobility and closed-loop control concept into the field of WSN [22]. A new mobile robot platform (MASmote) acting as a sensing or actuation node with mobility in mobile actuator sensor networks was presented in [23]. The system used a single MICA2 board, one interface board and two servo motors.

1.2.2 LOCALIZATION TECHNIQUES

1.2.2.1 Received Signal STRENGTH (RSS)

RSS refers to the signal strength of a radio signal received at a distance from the transmitter. The received signal strength decreases as the distance between the transmitter and receiver increases. The signal strength power is converted to distance using a mathematical model. Where the signal strength received is the input of the mathematical model and the output will be the relative distance between the two nodes based on the signal strength. While a particular RSS or connectivity measurement may be hard to predict, a statistical model for RSS and connectivity can be characterized [24].

A maximum likelihood - based (ML) received signal strength indication (RSSI)-based target tracking problem for an indoor area was presented in [25] where stationary anchor nodes were used to measure the RSSI of the target signal to estimate its location. An algorithm was developed in [26], where sensor nodes work as signposts for the robot to follow so the robot could successfully decide which node neighborhood it belongs to and avoid map generating of the environment. An adaptive Mobility-aware Sensor MAC protocol (MS-MAC) for mobile sensor applications was presented in [27], where a node detects its neighbor's mobility based on a change in its received signal level from the neighbor, or a loss of connection with this neighbor after a timeout period.

1.2.2.2 Time of Arrival (TOA)

Time of arrival is based on the reception time of the signal between nodes which is composed of the time of transmission in addition to a propagation time delay. Speed of light (speed of transmission of an RF signal) with TOA is used to measure the distance; however, this technique is affected by multipath signals and additive noise. The time needed for a signal transmitted by a node to reach the receiver node gives an indication of the relative distance between the two nodes which lead to using it for localization.

The use of passive and active nodes to solve the problem of positioning in cooperative networks was derived based on measurements in different nodes. An iterative algorithm to extract position information based on measurements collected by primary and secondary nodes where the primary nodes perform a two way – Time of Arrival estimation with the target and the secondary nodes used Time Difference of Arrival (TDOA) to estimate the location of the target [28].

Anchor nodes have been used as reference nodes for location estimation in multi-hop range based localization [29]. Mesh and cluster tree topologies were studied in cooperative and range based localization algorithms for Zigbee standard with RSSI method and the 802.15.4a standard with TOA technique.

In [30], a hybrid RSS and TOA localization algorithm was presented based on ray tracing channel modeling. The algorithm demonstrated an improved performance compared to conventional RSS and TOA algorithm.

Angle of Arrival (AoA) provides data about direction to the other nodes in the network rather than distance; it is calculated using both TOA and RSS techniques, so AoA could be used to help the earlier methods to improve their localization scheme [31].

1.2.2.3 Lateration

Using objects of well known locations to locate another object in the network is called lateration. Such objects are called anchor nodes which work as references and helps in location estimation. Each anchor node provides information about distance and coordinates which leads to a set of equations to help in the localization process [31]. In another terminology [28], such a method is called a hybrid method where anchor nodes are used to help other nodes in the network to approach their goal.

Implementing a hybrid wireless sensor network with a mixture of mobile robots and static sensors is a promising scenario for target localization. In such scenario, mobile robots and static sensor networks interact to detect environment changes and help each other to move the mobile motes to the desired goal; i.e. static sensors provide navigation information to guide mobile robots toward their goal positions. Localization in MASNet of a target and its tracking depends on the exact location information of the events that must be reported along with the event features. This depends on availability of precise knowledge of the location of the sensor nodes, mobile robots ability to execute actions more effectively in the region of detected agent, and the proper networking of all agents to share information.

A Timing-based Mobile Sensor Localization (TMSL) algorithm was discussed in [32]. For this scheme, in which sensor nodes determine their distances from actors by using propagation time and the known speed of radio frequency (RF) signals. In order to determine the distances, the mobile and static nodes broadcast reference beacons in a pattern of intervals adaptively defined according to the mobility of sensor nodes and the required level of localization accuracy. Another work proposed a hybrid autonomous sensor network for ambient intelligence applications using NMRC's 25mm wireless sensor node in conjunction with other sensor motes [33]. A hybrid wireless localization network based on Chirp Spread Spectrum (CSS) and ultrasonic positioning system (UPS) was developed in [8] to compensate weak points of each system and to resolve technical issues inherent to indoor mobile robot applications. Stationary UPS stations were used to provide the mobile robot with more information and help it localize.

Hybrid systems could be used in medical appliances to provide patients monitoring and support. It also could be used for aged and disabled people. In [34], a method of map building used graphical user interface (GUI), laser range finder and a camera are used to get information about the environment in which a mobile robot is moving to perform service tasks for aged and disabled persons. In [35], a hybrid sensor network of fixed and mobile nodes are used to monitor chronic patients and their environments where the mobile node is fixed to the patient for mobility and the fixed nodes are used to collect data about the environment and report in case of emergency.

A hybrid localization algorithm that introduces enhancements to wireless sensor networks by combining Classical Multi-Dimensional Scaling (CMDS) and Particle Spring Optimization (PSO) was proposed in [36]. The force-directed nature of the PSO algorithm relaxes the strict restrictions on inter-node distances, and allows for a tolerance that helps to distribute general trend of the topology layout.

As the hybrid localization system consists of static and mobile motes some motes can fail to communicate due to energy loss or technical problems a system for fault repair was proposed in [37]. Mobility equipped mobile sensors are utilized to recover or to improve the overall coverage and connectivity. RSSI is used to measure distance after selecting a mobile sensor as a redundant sensor to replace the dying sensor. A credit field based approach for mobile sensor navigation in a hybrid network of mobile and static sensors was presented in [38]. The credit field is stored locally in the static sensors and a distributed navigation algorithm is used to route the mobile sensor to the region of interest. Range free localization algorithm for wireless sensors in hybrid sensor networks was implemented in [39]. It consists of a large number of static sensors and relatively small number of mobile robots. The main objective was to maximize the network life time for an event driven sensor network.

Another tracking algorithm was proposed in [40]. A Slide Window Tracker (SWT) was used for tracking a maneuvering target in a noisy channel. Adjusting the window parameters could reduce the noise and track a fast target. The SWT algorithm could be used for tracking problem of unknown nonlinear time-varying measurements. Another localization for an acoustical source is studied in [41], where a hybrid model of Steered Response Pattern – phase transform (SRP - PHAT) and Spherical intersection (SX), in which SX creates a set of locations to be used by SRP-PHAT in order to reduce the computation cost.

Investigation on how to coordinate a team of mobile robots in order to deliver assistance services in a large logistic space is studied in [42], where the adopted robotic platform consists of a wheeled vehicle driven by electrical motors and with several sensors and with a WiFi node, mainly aimed at wireless communication with other robots and with a supervisor.

Despite the research efforts summarized above, characterization of localization error dynamics under the influence of different measurement error distributions continues to be an area of interest. In this research, we aim at characterizing localization error behavior given the number of motes with different signal to noise ratio (SNR) conditions and taking into account error propagation.

Previous work on localization was based mainly on positioning instruments such as GPS, Sonar's, or infrared data to help robots in localization for mobile robots or WSN alone. Hybrid implementation of mobile and WSN is still an area of active research. The use of signal strength based hybrid localization will be the subject of further investigation in this study. The study aims at having mobile robots that could localize and achieve their goal using information sent by the static nodes with precisely known locations. The static and dynamic motes emit an RF signal with a known and distinct frequency. Signal strength analysis under the effect of Additive Gaussian White Noise (AWGN) is used to estimate the distance between nodes. A study of mean square error (MSE) of the target estimation process using different schemes versus the signal to noise ratio is simulated in this research. Standard triangulation methods will be utilized to solve the localization problem for an overdetermined system. The static motes will help mobile motes to localize themselves relative to the target. No external systems are used in the localization process.

The rest of the thesis is organized as follows. Chapter 2 will present the proposed system description, while chapter 3 will discuss the localization algorithm and the mathematical model. In chapter 4, simulation results for different localization schemes will be presented and discussed. Finally, chapter 5 will present the conclusions.

Chapter 2 PROPOSED SYSTEM DESCRIPTION

2.1 SYSTEM BLOCK DIAGRAM

In this chapter, the structure and operation of the indoor localization problem is described. The system is composed of an ad-hoc network of static and dynamic motes. The static motes work as guiders for the dynamic motes which are looking for the target. In this thesis, computer simulation is used to simulate the localization problem of the dynamic motes and the target including the estimation of the location of the nodes and the target based on the signal strength analysis.

In figure 2-1, the main system diagram is shown which consists of a set of static and dynamic motes which collaborate to find the target. The static motes has fixed locations are used to localize the dynamic motes and provide the dynamic motes with information to localize the target. The dynamic motes are characterized with mobility in order to move toward the target, they rely on static motes in finding their locations. Dynamic motes can also find the target based on the information received by the static motes.

The target that emits a signal that provides the static and dynamic motes of information about its location. Localization of the target, based on the received signal strength, can be done using four schemes; namely using static motes only, dynamic motes only, static and dynamics for a co-hybrid model and a hybrid model. Figure 2-2 shows the system block diagram of the different schemes used in target localization.

Localization of dynamic motes and the target is done based on the received signal strength from the dynamic motes and the target where signal analysis of the received signal, a white Gaussian error added to the received signal are used in the model in order to find the relative distance and location.

The proposed system considers the channel shadowing problem based on both log-normal and uniform shadowing in which the signal power could follow a Gaussian distribution or a uniform distribution. Degradation in the signal strength of one of the static motes is proposed supposing that an object has been introduced as an obstacle in the environment.

Simulation for using the dynamic motes for localization of the target has been done as a second step, where all dynamic motes cooperate with each other to find an estimation of the target position based on the signal strength and the initial data received from the static motes.

A hybrid cooperative model has been simulated where the estimation of both static and dynamic motes have been taken in consideration, this model is preferred in case of signal lose where any of the static motes signal gets blocked due to an obstacle or out of charge. A Hybrid model has been implemented based on estimation of a dynamic node and a static node for the estimation of the target location.

The proposed system of the three dynamic motes attached to a wheel-robot, a number of static motes and a target which is initially a static target, further simulations could be done on dynamic target. The study of mean square error relation with the signal to noise ratio has been studied and simulated through this thesis for all simulations steps.

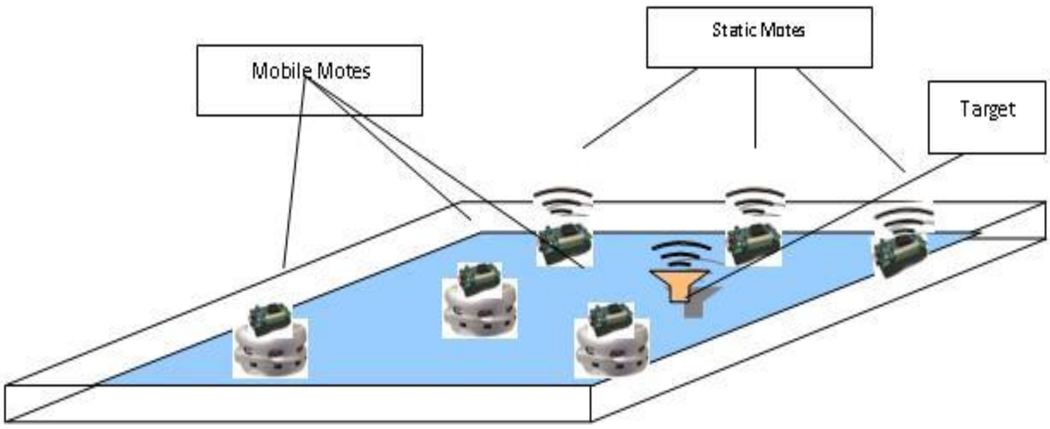

Figure 2-1: Schematic of the proposed ad-hoc wireless sensor network

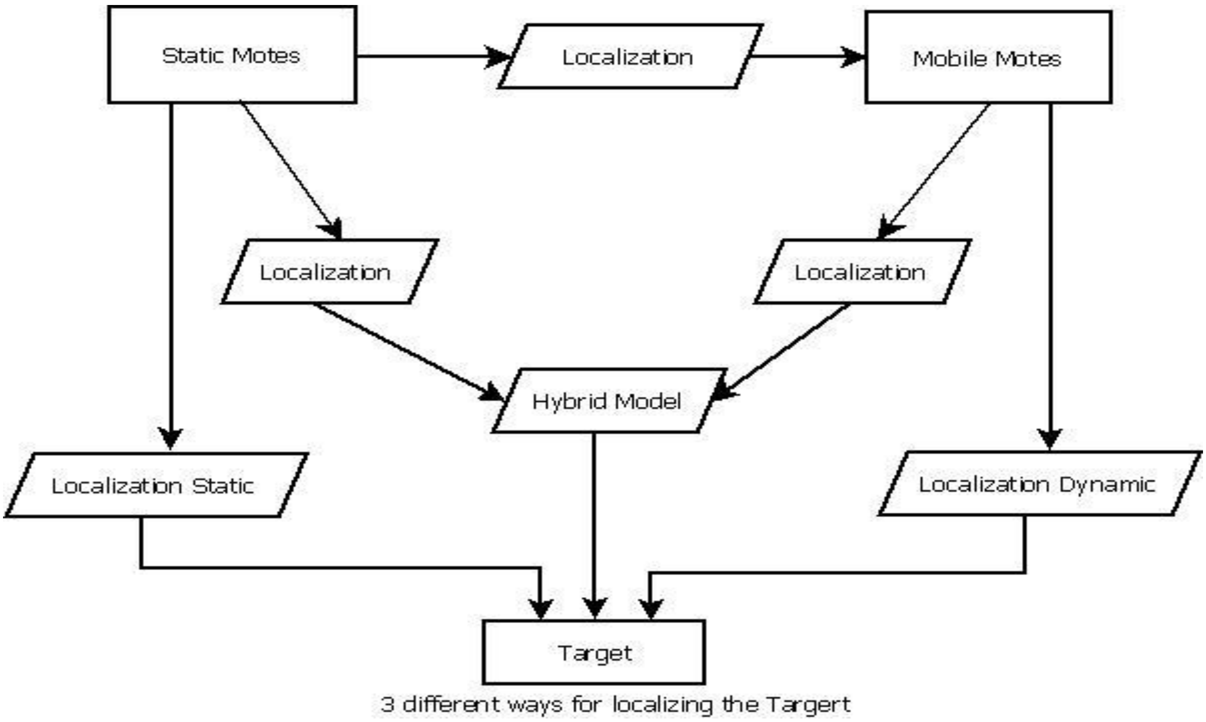

Figure 2-2: The System Block Diagram – Localization

2.2 PROPOSED LOCALIZATION MODEL

Figure 2-3 shows the general flow chart of the system model and the signal flow of the simulation as follows:

1. Initialize static motes:
   - Static motes can emit a radio signal and communicate with other motes in the environment; they know their precise location and the environment parameters.
2. Shadowing: when a mote has an obstacle in the way of its signal its SNR will be degraded, the following algorithms were simulated for the SNR shadowing
   a. Log normal Shadowing which follows a normal Gaussian Distribution for the shadowing with different values of σ^2.
   b. Uniform Shadowing where the shadowing of the mote will follow a uniform distribution, with variance σ^2.
3. RSS Estimation: the estimation of signal strength could be done based on the received signal, the propagation exponent and the initial estimation of the distance.
4. Localization Models and location estimation:
   a. Statics to localize dynamic motes: localization of the dynamic motes based on initial knowledge of the mobile motes position. The localization has been done based on the triangulation principle and the intersection of equations to result with the coordinates of the dynamic motes location.
   b. Target localization: the following methods were simulated for target localization based on initial data sent by the static motes to the dynamic motes.
      i. Static Motes Localization: Localization of the target using static motes which collaborate to find the estimation of the distance between themselves and the target and then find target coordinates.
      ii. Dynamic Motes Localization: the mobile could localize the location of the target based on the signal strength of the target and find the target coordinates accordingly.
      iii. Hybrid Model Localization: when using dynamic and static motes to estimate the location of the target position.
      iv. Co-Hybrid Localization: the target location is estimated based on both estimations from the static and dynamic motes

5. Calculation of mean square error versus signal to noise ratio for the different scenarios

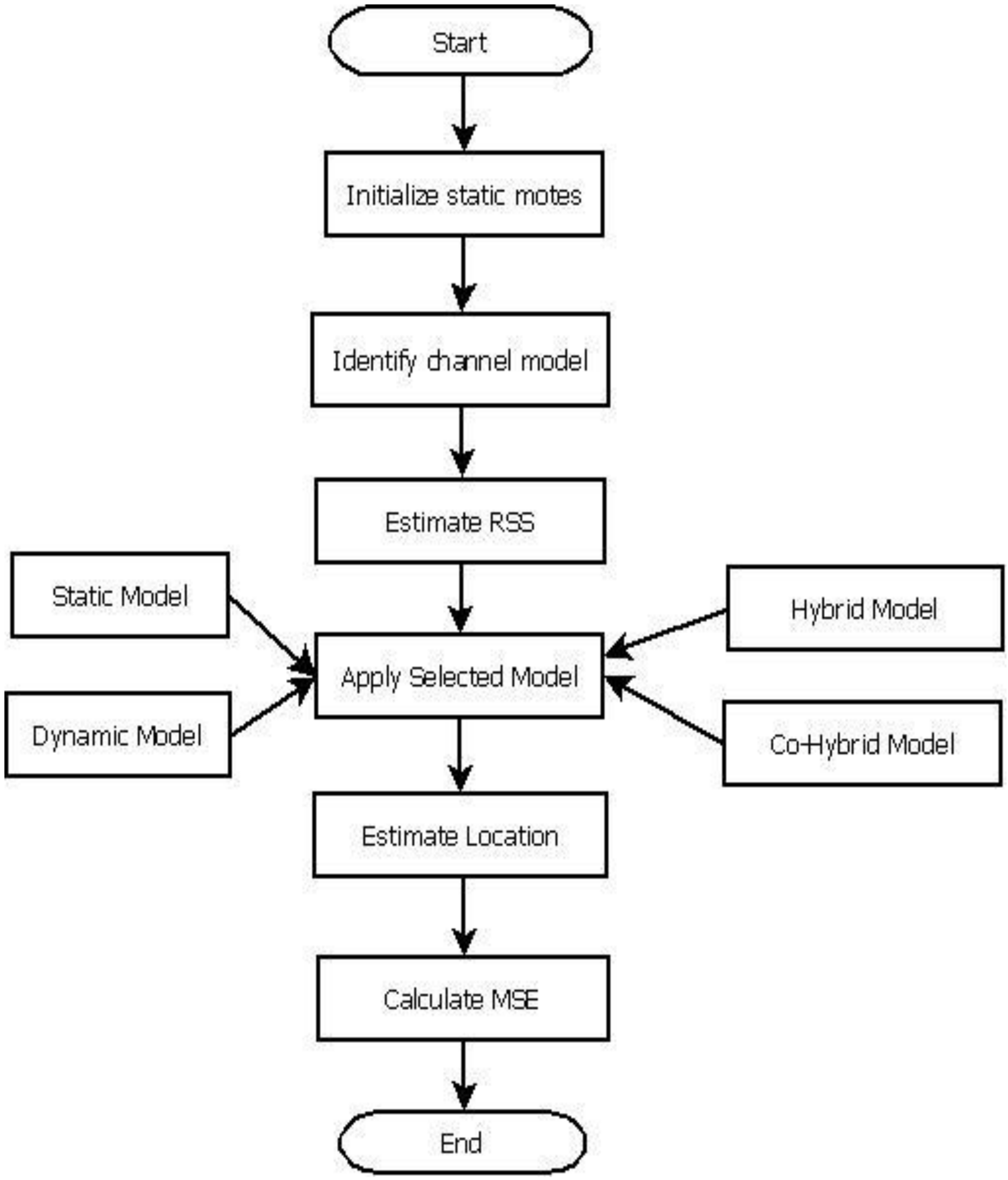

Figure 2-3: The Flowchart of the main system structure

Chapter 3 MATHEMATICAL MODEL

Localization based on triangulation was used with the following assumptions:

- Static motes have fixed known location.
- New distance estimation between static, dynamic and target are done with RSS. The following flowchart shows the estimation process algorithm with affect of AWGN.

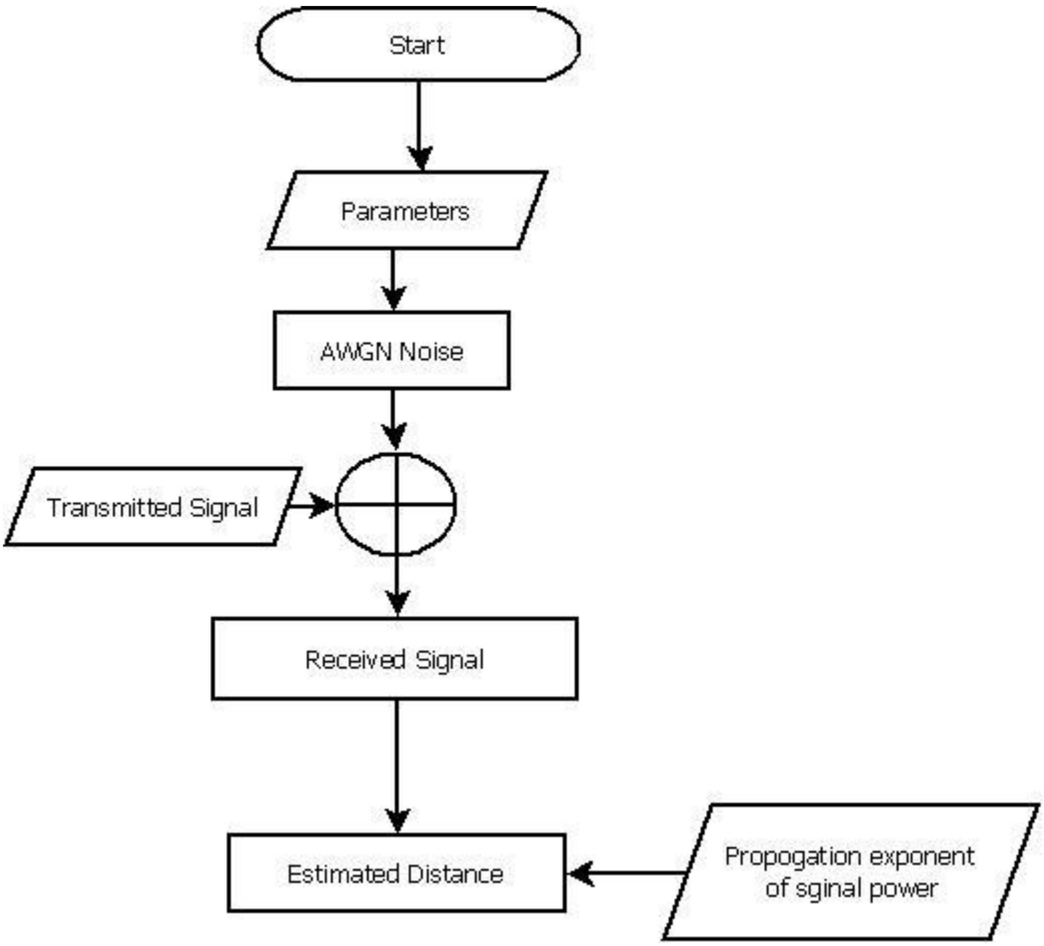

Figure 3-1: Flowchart for signal Strength analysis – Distance Estimation

- Static- Dynamic Distance: Initial Distances between static and dynamic motes are found using equation (1).

$$d_{ji}^{\;2} = (s_{xi} - d_{xj})^2 + (s_{yi} - d_{yj})^2 \qquad (1)$$

Where,

d_{ji} : the distance between Dynamic mote-j and static mote-i
s_{xi} : x-coordinates for the i-th static motes
s_{yi} : y-coordinates for the i-th static motes
d_{xj} : x-coordinates for the j-th dynamic motes
d_{yj} : y-coordinates for the j-th dynamic motes

- Distance Estimation (Static, Dynamic & Target): The model for estimating the distance for a given frequency for all motes and signal strength is:

$$D = (P_t / P_r)^{1/(2\times n)} \qquad (2)$$

Where,

D *is the estimated distance*

P_t *is the power of the transmitted signal*

P_r *is the power of the received signal*

n *is the propagation exponent*

An AWGN with a zero mean and varianceσ^2 is used to model the effect of the noise. The SNR is defined as the ratio of the received signal power over the noise power. The model above is repeated for each dynamic mote with a reference of a static mote.

For finding the target, the following was assumed:

- The static motes will find the target position and guide the dynamic motes to the target.
- The dynamic motes will start moving to the target using the given coordinates from the static based on finding the line equation between the nodes

The mathematical model is as follows:

- Dynamic motes Coordinates Estimation: To find the coordinates of the dynamic motes the following set of equations are used it was assumed that 3 static motes and 3 dynamic motes are used. The model can be generalized for other numbers.

$$\begin{aligned} D_{j1es}^2 &= (s_{x1} - u_j)^2 + (s_{y1} - v_j)^2 \\ D_{j2es}^2 &= (s_{x2} - u_j)^2 + (s_{y2} - v_j)^2 \\ D_{j3es}^2 &= (s_{x3} - u_j)^2 + (s_{y3} - v_j)^2 \end{aligned} \tag{3}$$

Where:

$d_{j1es}, d_{j2es}, d_{j3es}$: the estimated ditance between dynamic mote-j and static motes (1,2,3)
u_j : is the estimated x- coordinate of dynamic-j
v_j : is the estimated y- coordinate of dynamic-j

Equation (3) is used to find the initial distance between Dynamic node j and the static motes, simplifying equations in (3) we get

$$\begin{aligned} D_{j1es}^2 &= s_{x1}^2 + u_j^2 - 2\times s_{x1}u_j + s_{y1}^2 + v_j^2 - 2\times s_{y1}v_j \\ D_{j2es}^2 &= s_{x2}^2 + u_j^2 - 2\times s_{x2}u_j + s_{y2}^2 + v_j^2 - 2\times s_{y2}v_j \\ D_{j3es}^2 &= s_{x3}^2 + u_j^2 - 2\times s_{x3}u_j + s_{y3}^2 + v_j^2 - 2\times s_{y3}v_j \end{aligned} \tag{4}$$

By subtracting D_{j2es}^2 from D_{j2es}^2 we get

$$\begin{aligned} D_{j1es}^2 - D_{j2es}^2 &= s_{x1}^2 - s_{x2}^2 + s_{y1}^2 - s_{y2}^2 - 2\times s_{x1}u_j + 2\times s_{x2}u_j - 2\times s_{y1}v_j + 2\times s_{y2}v_j \\ D_{j1es}^2 - D_{j2es}^2 - s_{x1}^2 + s_{x2}^2 - s_{y1}^2 + s_{y2}^2 &= u_j(2(s_{x2} - s_{x1})) + v_j(2(s_{y2} - s_{y1})) \end{aligned} \tag{5}$$

Repeating the same procedure by subtracting D_{j3es}^2 from D_{j1es}^2 and simplifying we end up with the following matrix

$$\begin{pmatrix} D_{j1es}^2 - D_{j2es}^2 + s_{x2}^2 - s_{x1}^2 - s_{y1}^2 + s_{y2}^2 \\ D_{j1es}^2 - D_{j3es}^2 + s_{x3}^2 - s_{x1}^2 - s_{y1}^2 + s_{y3}^2 \end{pmatrix} = \begin{pmatrix} 2(s_{x2} - s_{x1}) & 2(s_{y2} - s_{y1}) \\ 2(s_{x3} - s_{x1}) & 2(s_{y3} - s_{y1}) \end{pmatrix} \begin{pmatrix} u_j \\ v_j \end{pmatrix} \tag{6}$$

In case one of the motes is missing: assuming static in the model (static mote 1 is missing)

$$\begin{pmatrix} D_{j2es}^2 - s_{x2}^2 - s_{y2}^2 - d_{xj}^2 - d_{yj}^2 \\ D_{j3es}^2 - s_{x3}^2 - s_{y3}^2 - d_{xj}^2 - d_{yj}^2 \end{pmatrix} = \begin{pmatrix} -2s_{x2} & -2s_{y2} \\ -2s_{x3} & -2s_{y3} \end{pmatrix} \begin{pmatrix} u_j \\ v_j \end{pmatrix} \qquad (7)$$

- Target Coordinates: the model for finding the coordinates of the target is similar for finding it for the dynamic, it could be done using:
    a. Static motes: Static motes for localizing the target coordinates based on triangulation.

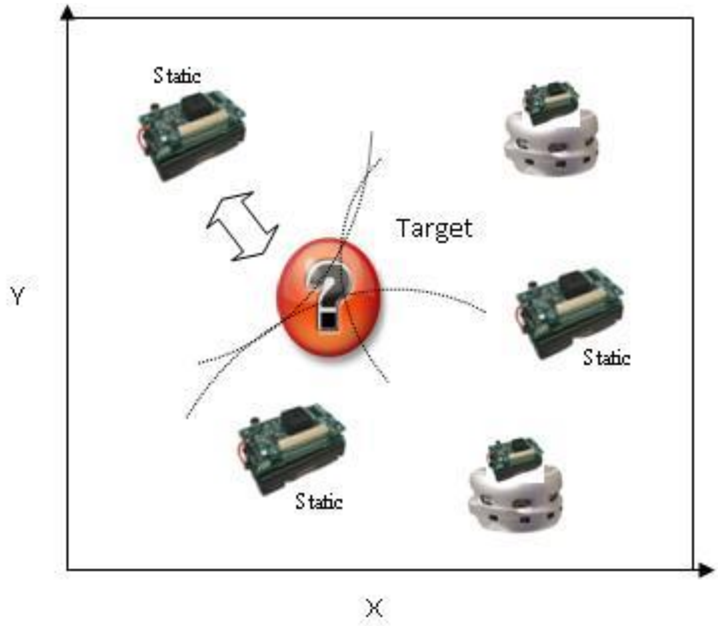

Figure 3-2: Target Localization

(u_t, v_t): are the target estimated coordinates:

$$\begin{pmatrix} D_{s1tes}^2 - D_{s2tes}^2 - s_{x1}^2 - s_{y1}^2 + s_{x2}^2 + s_{y2}^2 \\ D_{s2tes}^2 - D_{s3tes}^2 + s_{x3}^2 - s_{x2}^2 - s_{y2}^2 + s_{y3}^2 \end{pmatrix} = \begin{pmatrix} 2(s_{x2} - s_{x1}) & 2(s_{y2} - s_{y1}) \\ 2(s_{x3} - s_{x2}) & 2(s_{y3} - s_{y2}) \end{pmatrix} \begin{pmatrix} u_t \\ v_t \end{pmatrix} \qquad (8)$$

b. Dynamic motes: based on dynamic motes triangulation.

$$\begin{pmatrix} D_{jtes}^2 - D_{j+1tes}^2 - u_1^2 - v_1^2 + u_2^2 + v_2^2 \\ D_{j+1tes}^2 - D_{j+2tes}^2 + u_3^2 - u_2^2 - v_2^2 + v_3^2 \end{pmatrix} = \begin{pmatrix} 2(u_2 - u_1) & 2(v_2 - v_1) \\ 2(u_3 - u_2) & 2(v_3 - v_2) \end{pmatrix} \begin{pmatrix} u_t \\ v_t \end{pmatrix} \qquad (9)$$

The above matrices and system were derived as follows (D_{sites} for i= 1, 2, 3 is the estimated distance between static motes and the target)

- Using static motes: for static node i.

$$
\begin{aligned}
D_{sites}^{2} &= (s_{xi} - u_{t})^{2} + (s_{yi} - v_{t})^{2} \\
D_{si+1tes}^{2} &= (s_{xi+1} - u_{t})^{2} + (s_{yi+1} - v_{t})^{2} \\
D_{si+2tes}^{2} &= (s_{xi+2} - u_{t})^{2} + (s_{yi+2} - v_{t})^{2}
\end{aligned} \tag{10}
$$

(u_t , v_t): estimated location of the target.

By simplifying the equations in (10)

$$
\begin{aligned}
D_{sites}^{2} &= s_{xi}^{2} + u_{t}^{2} - 2\times s_{xi}u_{t} + s_{yi}^{2} + v_{t}^{2} - 2\times s_{yi}v_{t} \\
D_{si+1tes}^{2} &= s_{xi+1}^{2} + u_{t}^{2} - 2\times s_{xi+1}u_{t} + s_{yi+1}^{2} + v_{t}^{2} - 2\times s_{yi+1}v_{t} \\
D_{si+2tes}^{2} &= s_{xi+2}^{2} + u_{t}^{2} - 2\times s_{xi+2}u_{t} + s_{yi+2}^{2} + v_{t}^{2} - 2\times s_{yi+2}v_{t}
\end{aligned} \tag{11}
$$

By subtracting the $D_{si+1tes}^{2}$ from D_{sites}^{2} we get

$$
\begin{aligned}
D_{sites}^{2} - D_{si+1tes}^{2} &= s_{xi}^{2} - s_{xi+1}^{2} - 2\times s_{xi}u_{t} + 2\times s_{xi+1}u_{t} + s_{yi}^{2} - s_{yi+1}^{2} - 2\times s_{yi}v_{t} + 2\times s_{yi+1}v_{t} \\
D_{sites}^{2} - D_{si+1tes}^{2} - s_{xi}^{2} + s_{xi+1}^{2} - s_{yi}^{2} + s_{yi+1}^{2} &= u_{t}(2(s_{xi+1} - s_{xi})) + v_{t}(2(s_{yi+1} - s_{yi}))
\end{aligned} \tag{12}
$$

By subtracting $D_{si+2tes}^{2}$ from D_{sites}^{2} we get

$$
\begin{aligned}
D_{si+1tes}^{2} - D_{si+2tes}^{2} &= s_{xi+1}^{2} - s_{xi+2}^{2} - 2\times s_{xi+1}u_{t} + 2\times s_{xi+2}u_{t} + s_{yi+1}^{2} - s_{yi+2}^{2} - 2\times s_{yi+1}v_{t} + 2\times s_{yi+1}v_{t} \\
D_{si+1tes}^{2} - D_{si+2tes}^{2} - s_{xi+1}^{2} + s_{xi+2}^{2} - s_{yi+1}^{2} + s_{yi+2}^{2} &= u_{t}(2(s_{xi+2} - s_{xi+1})) + v_{t}(2(s_{yi+2} - s_{yi+1}))
\end{aligned} \tag{13}
$$

by simplifying equations (12) and (13)

$$
\begin{pmatrix} D_{sites}^{2} - D_{s2tes}^{2} - s_{xi}^{2} - s_{yi}^{2} + s_{x2}^{2} + s_{y2}^{2} \\ D_{si+1tes}^{2} - D_{si+2tes}^{2} + s_{xi+2}^{2} - s_{xi+1}^{2} - s_{yi+1}^{2} + s_{yi+2}^{2} \end{pmatrix} = \begin{pmatrix} 2(s_{x2} - s_{xi}) & 2(s_{y2} - s_{yi}) \\ 2(s_{xi+2} - s_{xi+1}) & 2(s_{yi+2} - s_{yi+1}) \end{pmatrix} \begin{pmatrix} u_{t} \\ v_{t} \end{pmatrix} \tag{14}
$$

- Using Dynamic motes: for Dynamic node j.

$$
\begin{aligned}
D_{djtes}^{2} &= (u_{j} - u_{t})^{2} + (v_{j} - v_{t})^{2} \\
D_{dj+1tes}^{2} &= (u_{j+1} - u_{t})^{2} + (v_{j+1} - v_{t})^{2} \\
D_{d3j+2tes}^{2} &= (u_{j+2} - u_{t})^{2} + (v_{j+2} - v_{t})^{2}
\end{aligned} \tag{15}
$$

By simplifying equations in (15)

$$
\begin{aligned}
D_{djtes}^{2} &= u_{j}^{2}+u_{t}^{2}-2\times u_{j}u_{t}+v_{j}^{2}+v_{t}^{2}-2\times v_{j}v_{t} \\
D_{dj+1tes}^{2} &= u_{j+1}^{2}+u_{t}^{2}-2\times u_{j+1}u_{t}+v_{j+1}^{2}+v_{t}^{2}-2\times v_{j+1}v_{t} \\
D_{dj+2tes}^{2} &= u_{j+2}^{2}+u_{t}^{2}-2\times u_{j+2}u_{t}+v_{j+2}^{2}+v_{t}^{2}-2\times v_{j+2}v_{t}
\end{aligned}
\quad (16)
$$

By subtracting $D_{dj+1tes}^{2}$ from D_{djtes}^{2}

$$
\begin{aligned}
&D_{djtes}^{2}-D_{dj+1tes}^{2}=u_{j}^{2}-u_{j+1}^{2}-2\times u_{j}u_{t}+2\times u_{j+1}u_{t}+v_{j}^{2}-v_{j+1}^{2}-2\times v_{j}v_{t}+2\times v_{j+1}v_{t} \\
&D_{djtes}^{2}-D_{dj+1tes}^{2}-u_{j}^{2}+u_{j+1}^{2}-v_{j}^{2}+v_{j+1}^{2}=u_{t}(2(u_{j+1}-u_{j}))+v_{t}(2(v_{j+1}-v_{j}))
\end{aligned}
\quad (17)
$$

By subtracting $D_{dj+2tes}^{2}$ from $D_{dj+1tes}^{2}$

$$
\begin{aligned}
&D_{dj+1tes}^{2}-D_{dj+2tes}^{2}=u_{j+1}^{2}-u_{j+2}^{2}-2\times u_{j+2}u_{t}+2\times u_{j+2}u_{t}+v_{j+1}^{2}-v_{j+2}^{2}-2\times v_{j+1}v_{t}+2\times v_{j+1}v_{t} \\
&D_{dj+1tes}^{2}-D_{dj+2tes}^{2}-u_{j+1}^{2}+u_{j+2}^{2}-v_{j+1}^{2}+v_{j+2}^{2}=u_{t}(2(u_{j+2}-u_{j+1}))+v_{t}(2(v_{j+2}-v_{j+1}))
\end{aligned}
\quad (18)
$$

The final equation

$$
\begin{pmatrix}
D_{djtes}^{2}-D_{dj+1tes}^{2}-u_{j}^{2}-v_{j}^{2}+u_{j+1}^{2}+v_{j+1}^{2} \\
D_{dj+1tes}^{2}-D_{dj+2tes}^{2}+u_{j+2}^{2}-u_{j+1}^{2}-v_{j+1}^{2}+v_{j+2}^{2}
\end{pmatrix}
=
\begin{pmatrix}
2(u_{j+1}-u_{j}) & 2(v_{j+1}-v_{1}) \\
2(u_{j+2}-u_{j+1}) & 2(v_{j+2}-v_{j+1})
\end{pmatrix}
\begin{pmatrix}
u_{t} \\
v_{t}
\end{pmatrix}
\quad (19)
$$

Chapter 4 SIMULATION RESULTS

In this chapter, simulation results of the different schemes proposed in this thesis will be presented. First, we will start with dynamic nodes localization. Then, the results of target localization using static motes only, dynamic motes only, hybrid model, and cooperative hybrid model will be presented. Finally, the effect of wireless channel shadowing will be discussed under log-normal and uniform shadowing distributions. The different schemes will be compared based on the MSE criterion for different signal to noise ratio values.

4.1 SIMULATION PARAMETERS

In the results below, the simulation has been done based on the following parameters:

- SNR varies between 5 to 25 dB.
- Number of simulations per experiment is 1000.
- Noise added to the received signal from the motes and the target follows the additive white Gaussian noise model.
- The received signal is simulated to be as a continuous radio frequency signal with a specific frequency and amplitude.
- The power of the received signal is directly proportional to the transmitted signal power and inversely to the distance (D) according to the following model, where n is the path loss exponent assumed to be 2.

$$p_r \propto \frac{p_t}{D^n} \tag{20}$$

- Three static and three dynamic motes are used.

In all figures presented later, the following legend is used

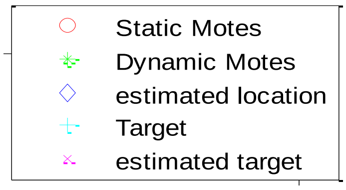

Figure 4-1: Legend for figures

4.1.1 *USING ALL STATIC MOTES IN THE DYNAMIC MOTES ESTIMATION PROCESS*

As the static motes location are known (fixed) and the dynamic motes locations are generated randomly, first, the estimated locations for the dynamic motes were found for different SNR values (from 5 – 25 dB).

In figure 4-2, the estimation is done using the three static motes with an SNR value of 5. It is noticed that there is a significant error in the estimated location because of the high noise levels.

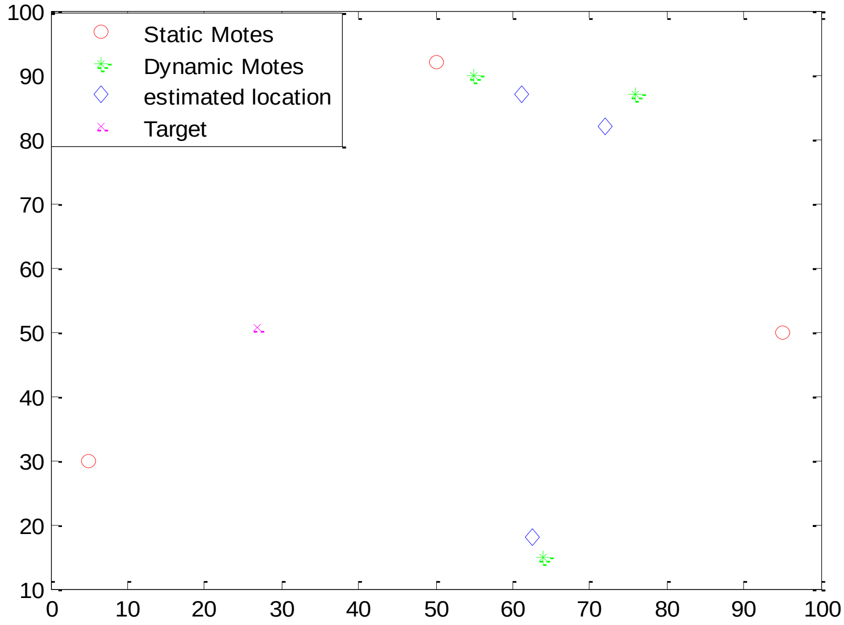

Figure 4-2: Estimated location of dynamic motes using 3- static motes and SNR=5 dB

Figure 4-3 shows a more accurate estimation as the signal strength increases to 10 dB.

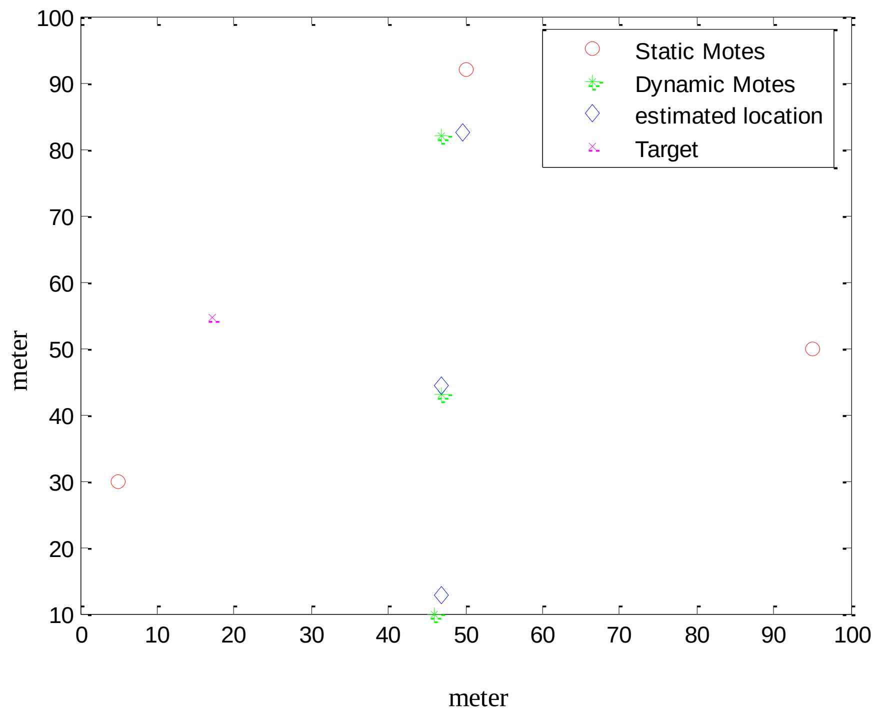

Figure 4-3: Estimated Location of Dynamic motes using 3-static motes, SNR=10

As the value of SNR increases further, the estimation of the dynamic mote locations will be more accurate as shown in figures 4-4 to figure 4-6.

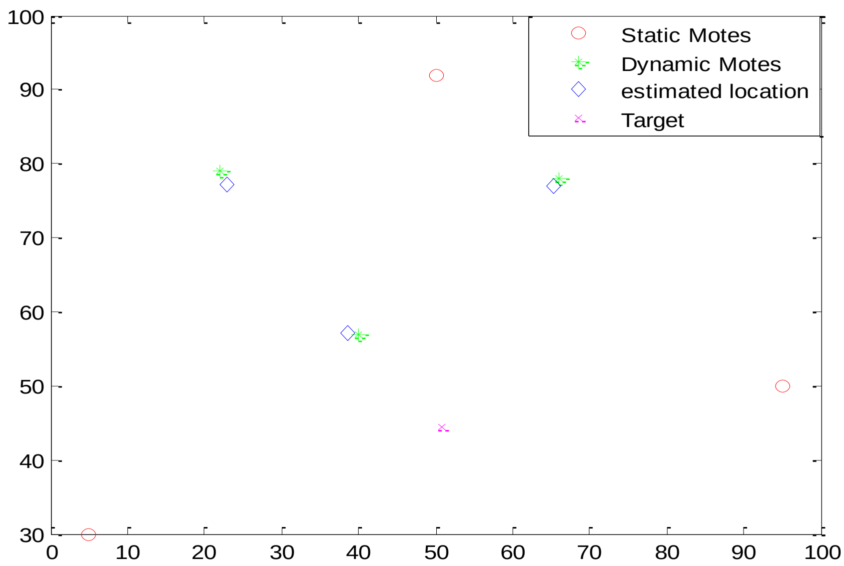

Figure 4-4: Estimated Location of Dynamic motes using 3-static motes, SNR=15

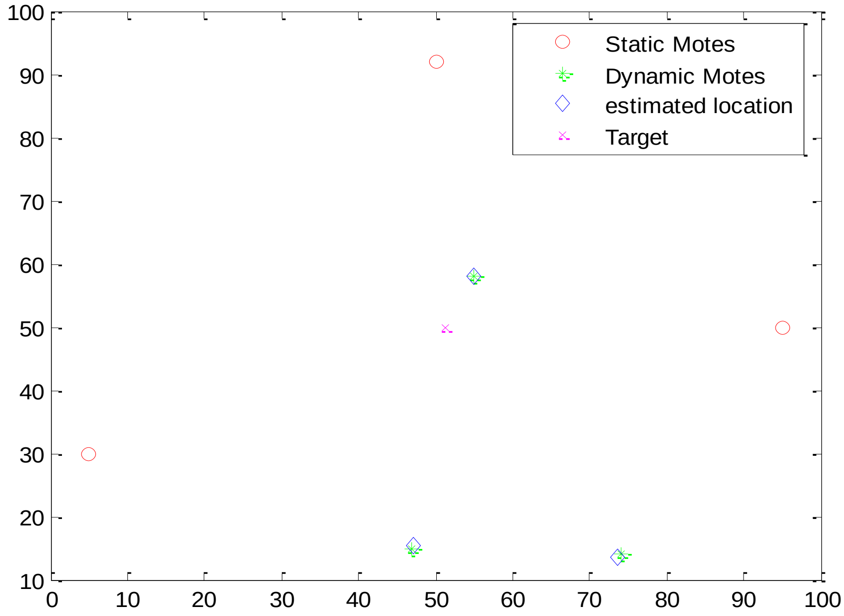

Figure 4-5: Estimated Location of Dynamic motes using 3-static motes, SNR=20

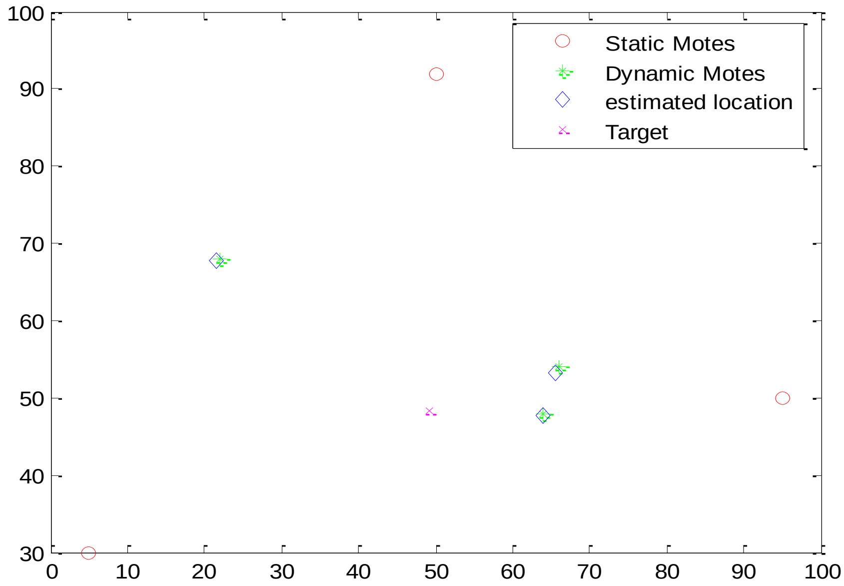

Figure 4-6: Estimated Location of Dynamic motes using 3-static motes, SNR=25

In figure 4-6, the histograms of the error in the x and y coordinates are shown for the dynamic motes with SNR of 25 dB. It is observed that the errors tend to follow a normal distribution.

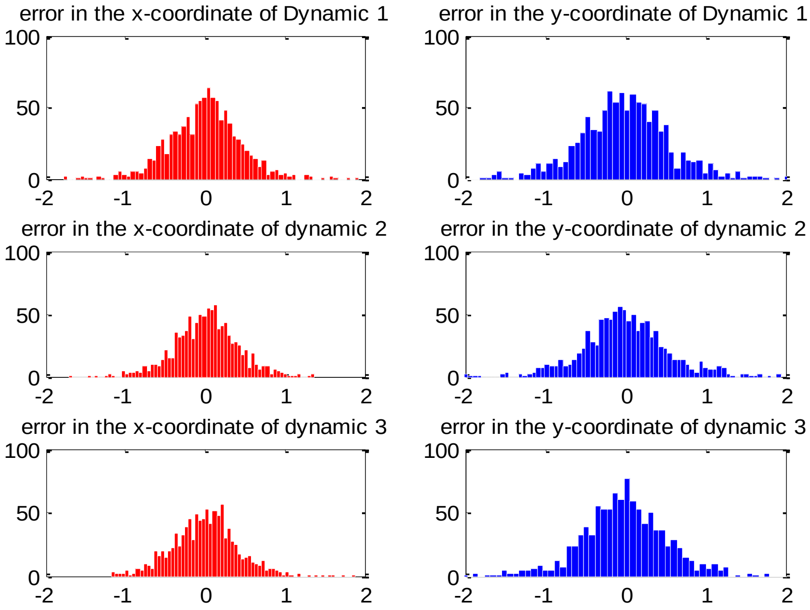

Figure 4-7: The error in estimating the locations of dynamic motes with SNR=25

A similar observation is made from figure 4-7 for an SNR of 5 dB but it is noticed that the variance of the distribution tends to be larger.

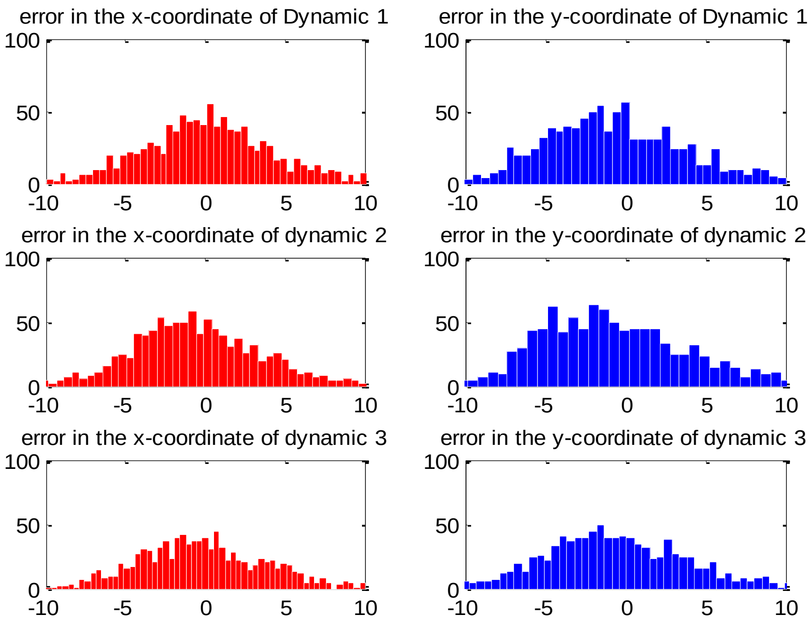

Figure 4-8: The error in estimating the locations of dynamic motes with SNR=5

The results above show an accurate estimation of the dynamic motes locations which improve as the value of SNR increases. It is also observed that the error follows a normal distribution where the error variance has been significantly reduced by increasing the SNR value from 5 to 25 dB.

4.2 TARGET LOCALIZATION

Based on a signal from the target, localization could be done using static, dynamic or a hybrid approach in which collaboration between both static and dynamic motes takes place.

4.2.1 LOCALIZATION OF TARGET USING STATIC MOTES:

Static motes could be used to localize the target and estimate its location for different SNR conditions as shown in figures 4-9 to 4-18. It is clear that using static motes results in good estimation of the target position, even for low values of SNR. This is attributed to the fact that the static motes have fixed known locations and there is no error propagation in the estimation process.

Figure 4-19 shows the MSE versus the signal to noise ratio where the results have shown very good performance even under low SNR values.

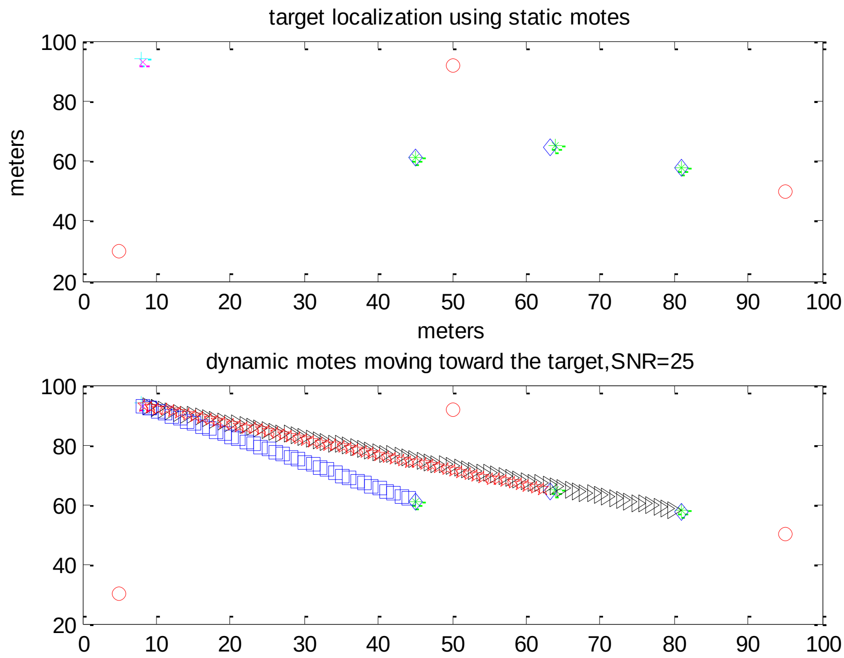

Figure 4-9: Target localization using static motes, SNR=5 dB

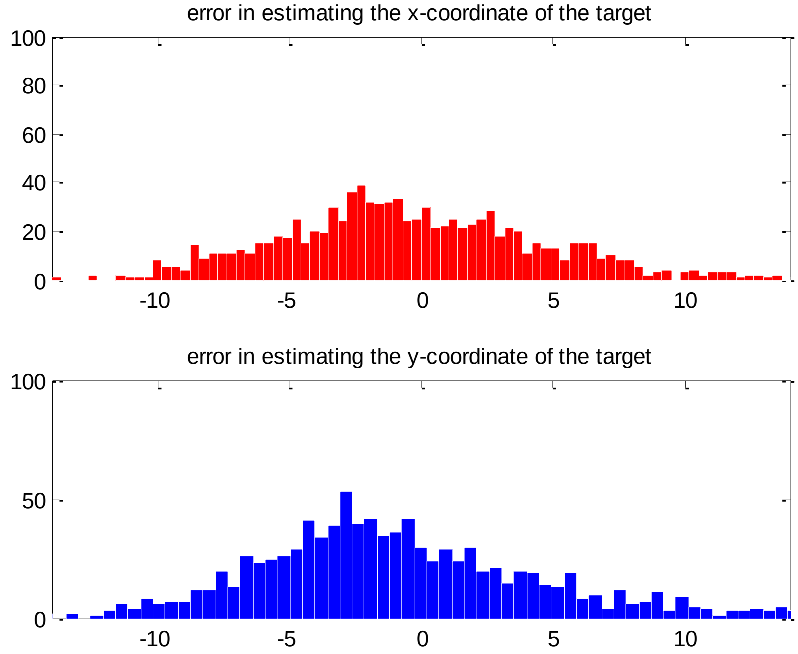

Figure 4-10: error in localizing the target coordinates using static motes with SNR=5 dB

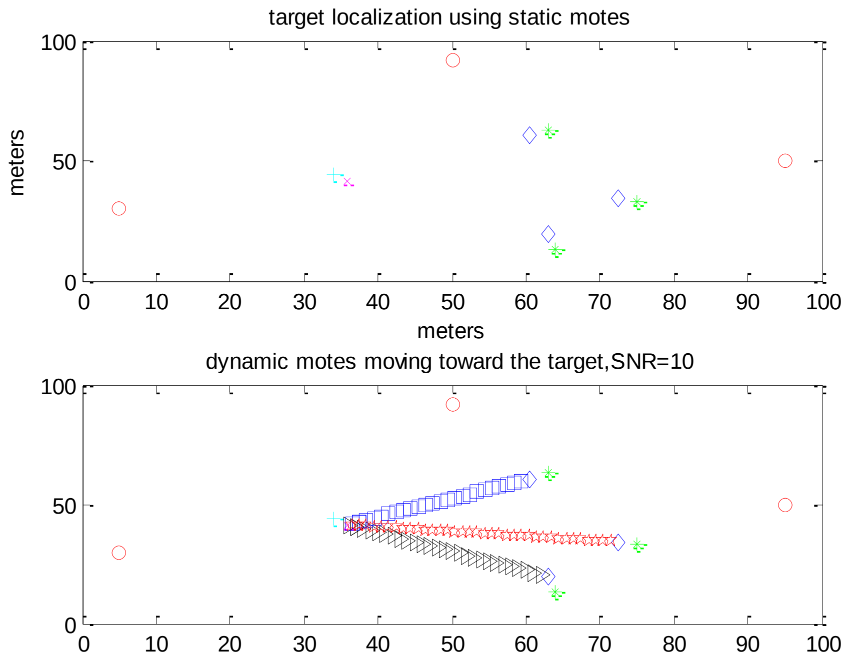

Figure 4-11: target localization using static motes, SNR=10 dB

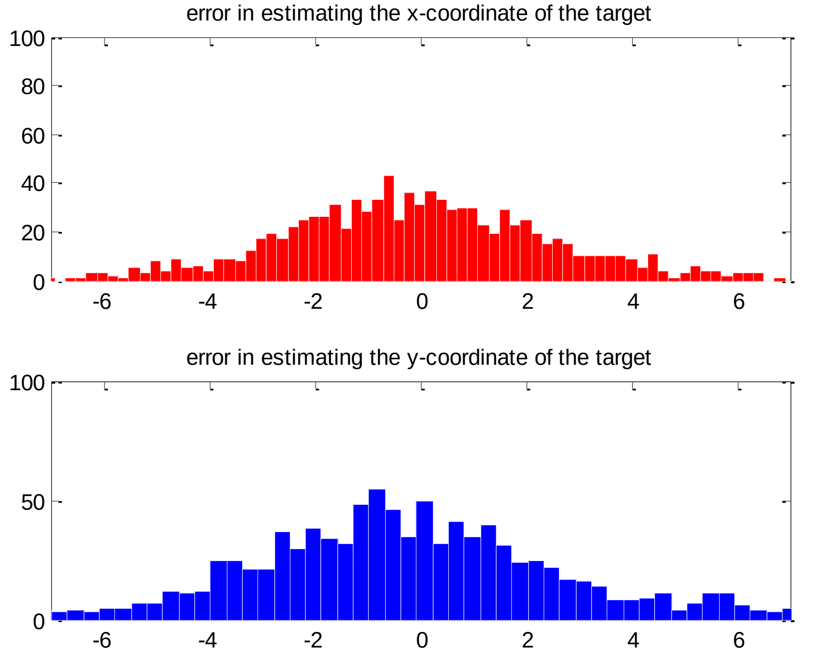

Figure 4-12: error in localizing the target coordinates using static motes with SNR=10 dB

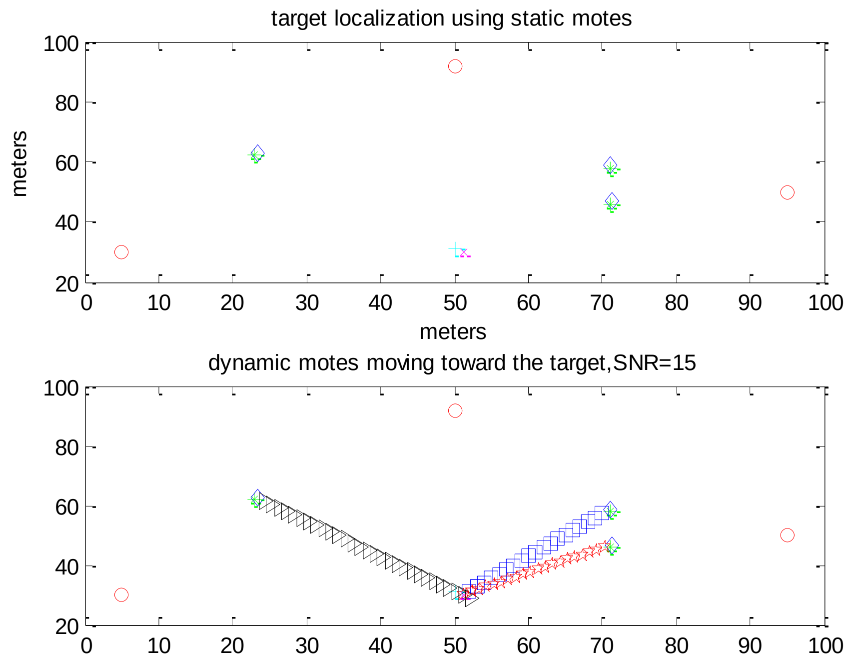

Figure 4-13: target localization using static motes, SNR=15 dB

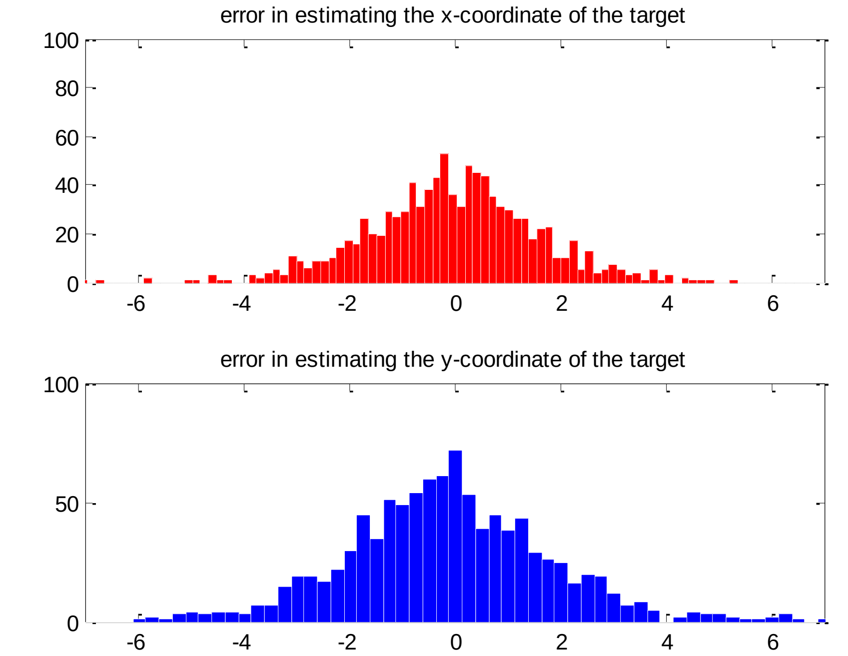

Figure 4-14: error in localizing the target coordinates using static motes with SNR=15 dB

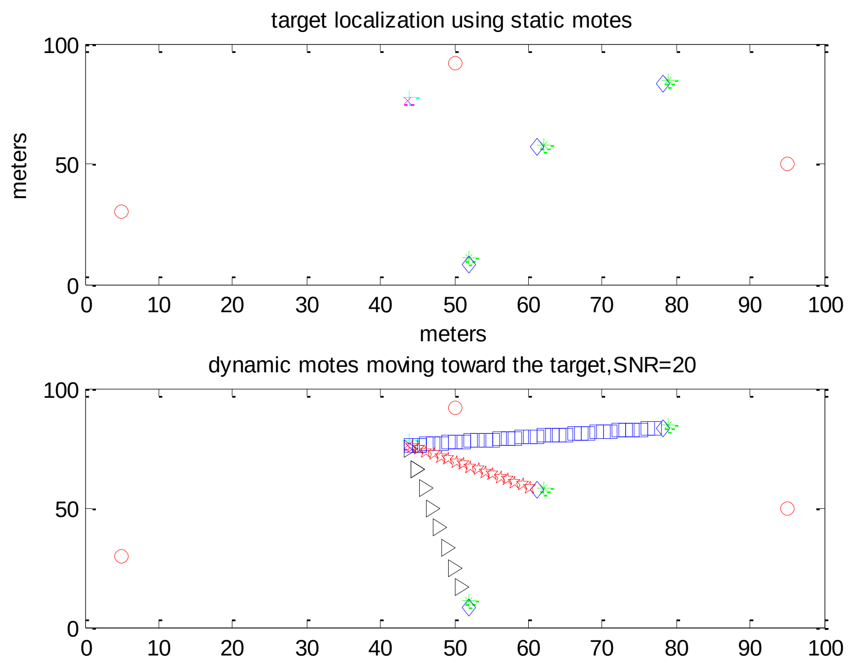

Figure 4-15: target localization using static motes, SNR=20 dB

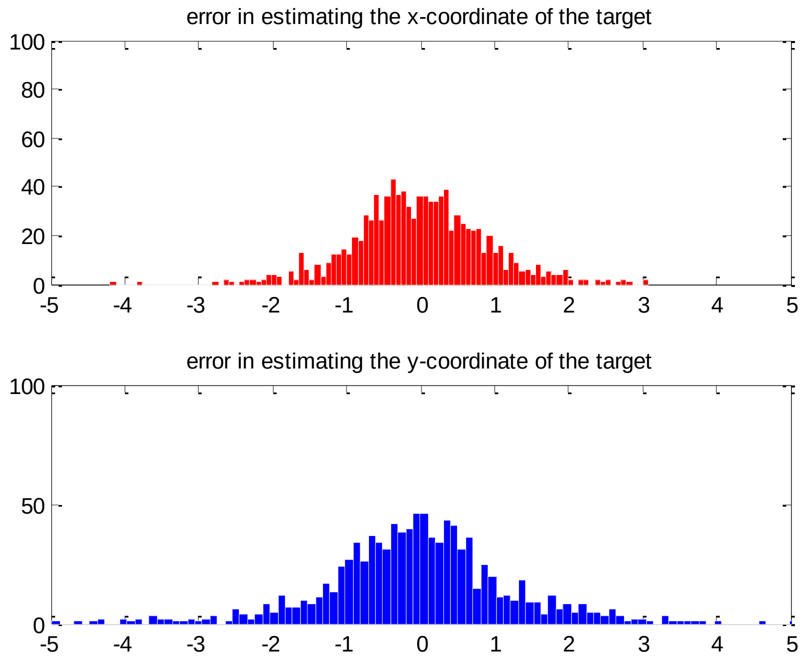

Figure 4-16: error in localizing the target coordinates using static motes with SNR=20 dB

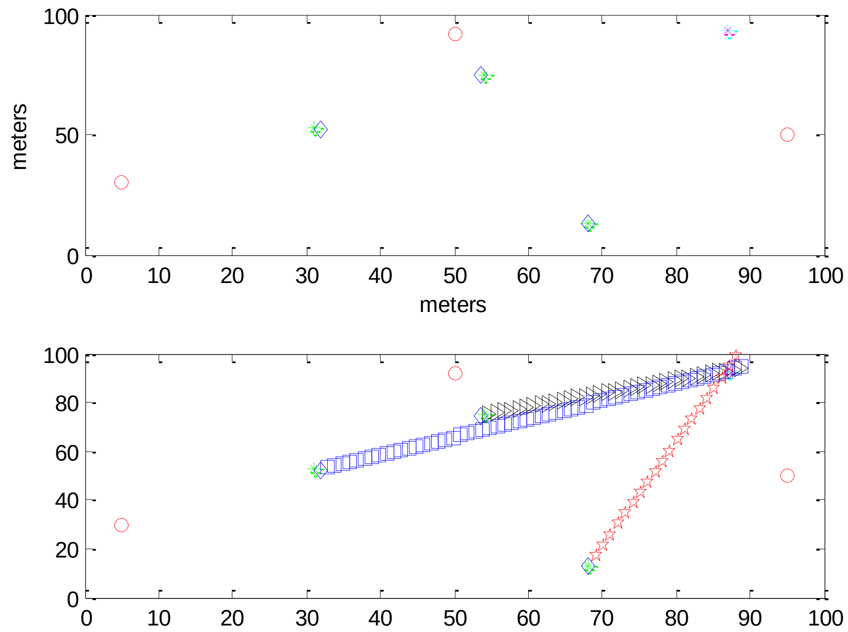

Figure 4-17: target localization using static motes, SNR=25 dB

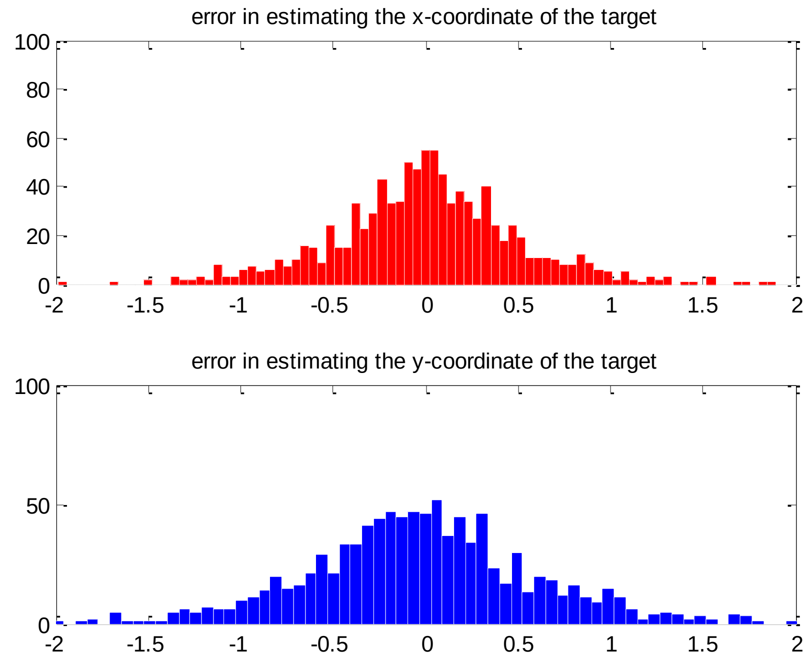

Figure 4-18: error in localizing the target coordinates using static motes with SNR=25 dB

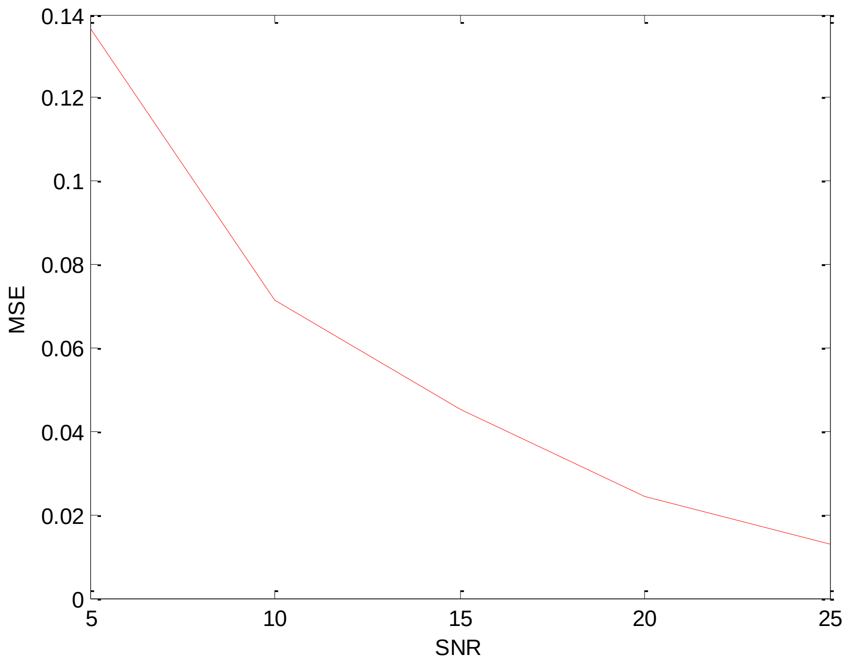

Figure 4-19: MSE vs. SNR (localization of target using static motes)

4.2.2 LOCALIZATION OF TARGET USING DYNAMIC MOTES:

Localization of target based on dynamic motes with different signal strengths from the target is considered in the set of simulations shown in figures 4-20 to 4-36.

The results show that accurate estimation of the target is achievable but with high SNR (e.g. an SNR of 25 dB). It is observed that to achieve the same MSE as the static motes case, the dynamic motes performance suffers a significant degradation (20 dB for a MSE of 0.1).

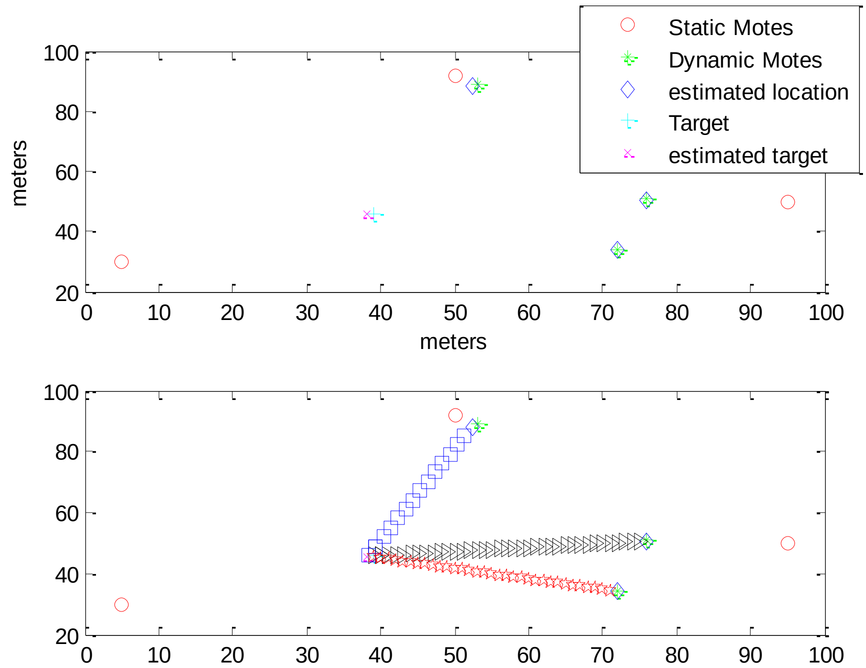

Figure 4-20: target localization using dynamic motes, SNR=25 dB

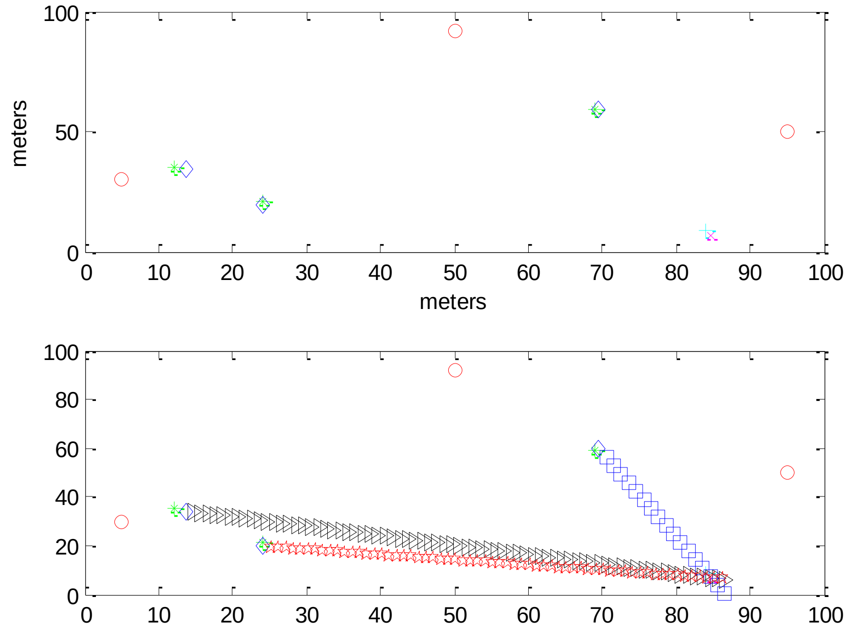

Figure 4-21: target localization using dynamic motes, SNR=20 dB

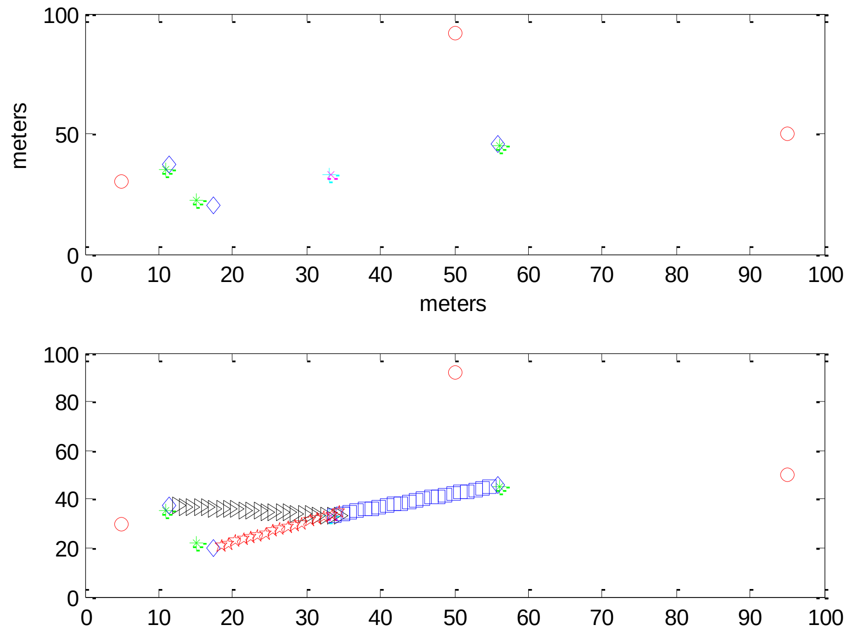

Figure 4-22: target localization using dynamic motes, SNR=15 dB

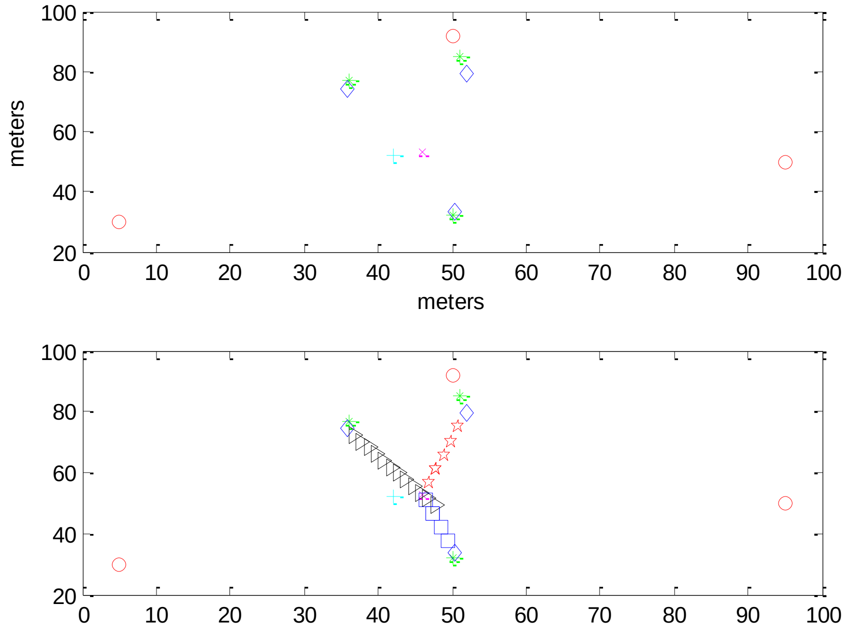

Figure 4-23: target localization using dynamic motes, SNR=10 dB

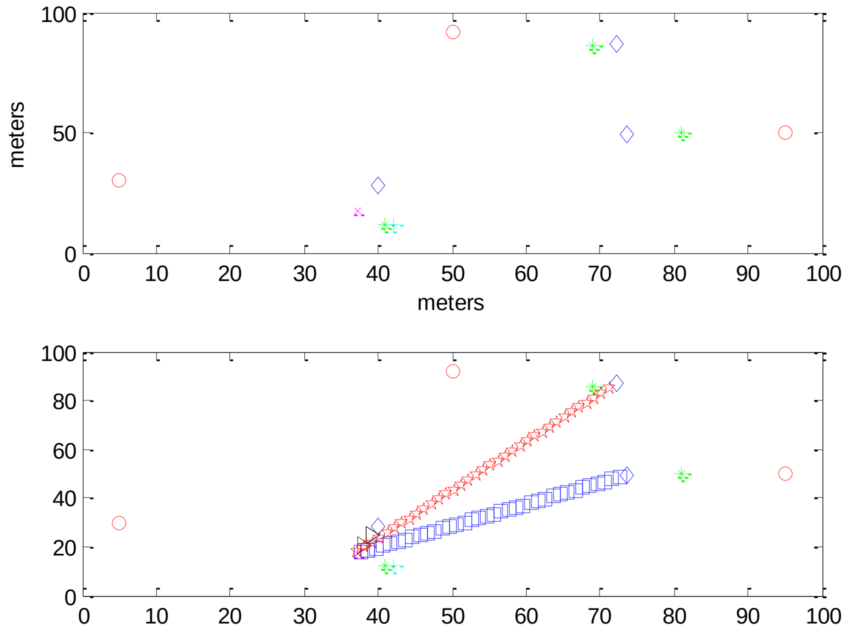

Figure 4-24: target localization using dynamic motes, SNR=5 dB

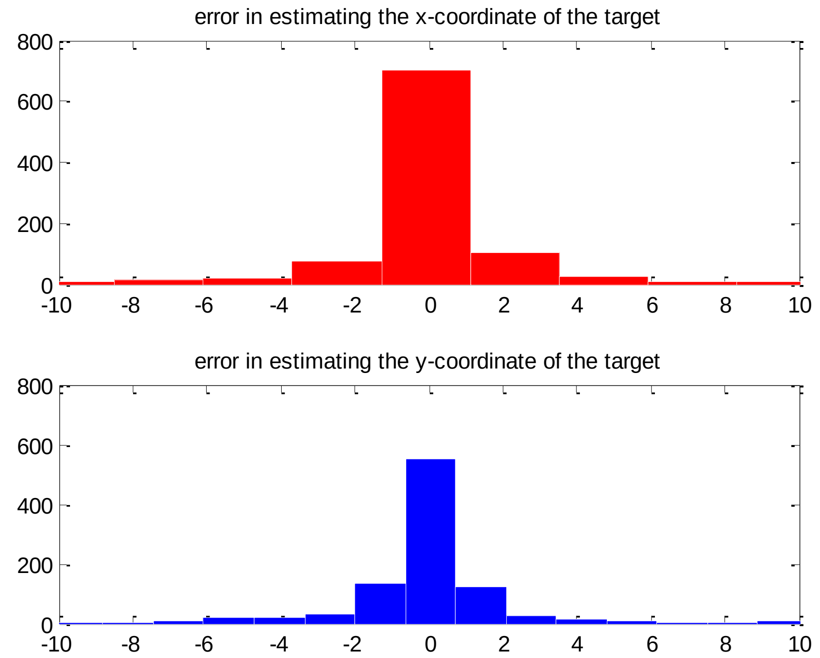

Figure 4-25: error in localizing the target with dynamic motes, SNR=25

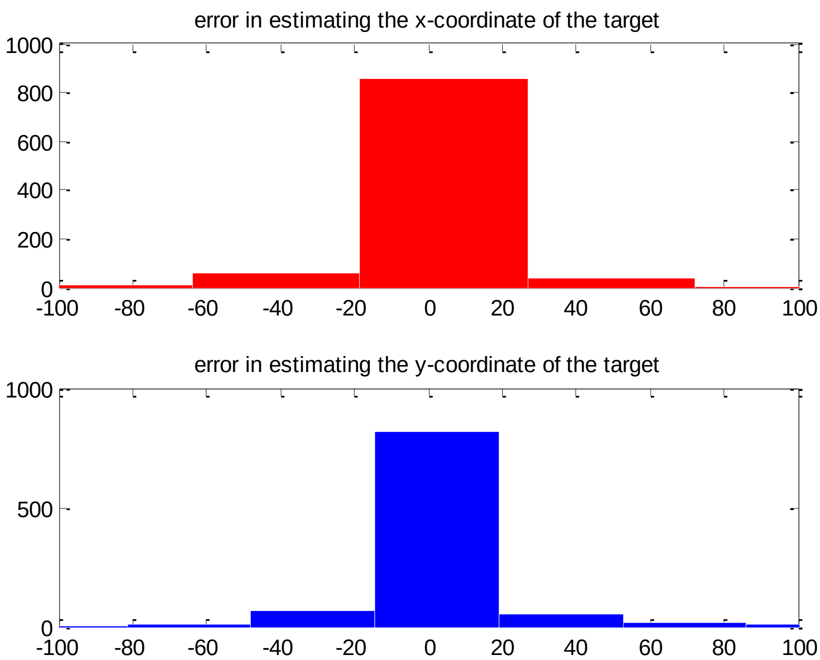

Figure 4-26: error in localizing the target with dynamic motes, SNR=5

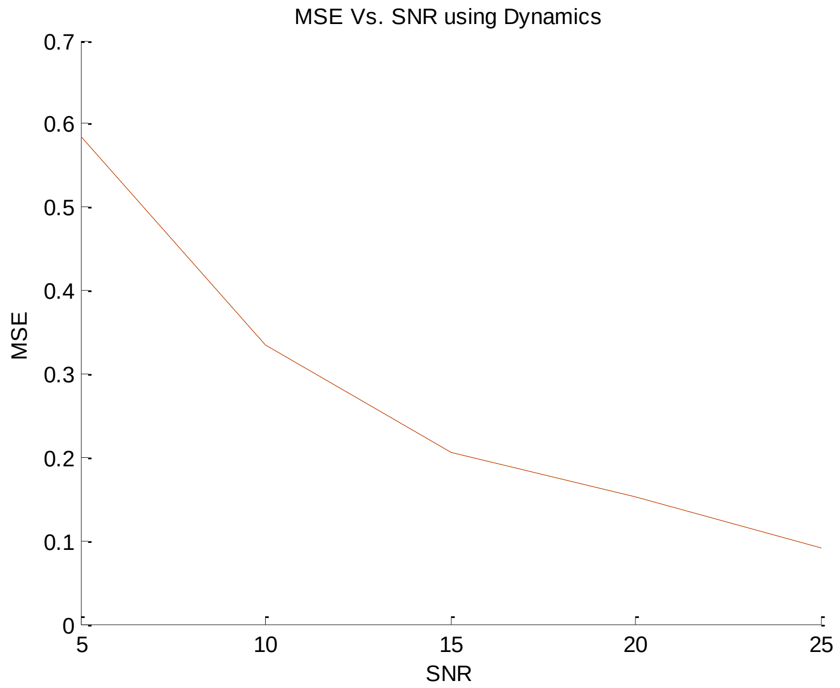

Figure 4-27: MSE vs. SNR (localization of target using dynamic motes)

Based on the previous results, it can be concluded that dynamic motes bases scheme does not provide accurate performance and a large value of SNR is needed (more transmitted power is needed).

4.2.3 *ESTIMATION OF TARGET, ONE STATIC MOTE IS OUT OF RANGE:*

In case of failure of one static mote, as it could happen in real life networks where one node could stop responding or could be out of range of an ad-hoc – network, a simulation has been done to show the impact on estimating the locations for the dynamic motes. This scenario also describes the case when a node is out of power due to battery drainage. The simulation is done over different values of SNR, varying from 5-25 dB, as shown in the figures below. We have only two static motes which will communicate with each dynamic in order to estimate the relative distance and relative coordinates. It is found that the error in estimating the dynamic motes coordinates has increased with low signal strength when one mote is missing, although increasing the signal strength will reduce the error as shown in figure 4-21 for an SNR value of 25.

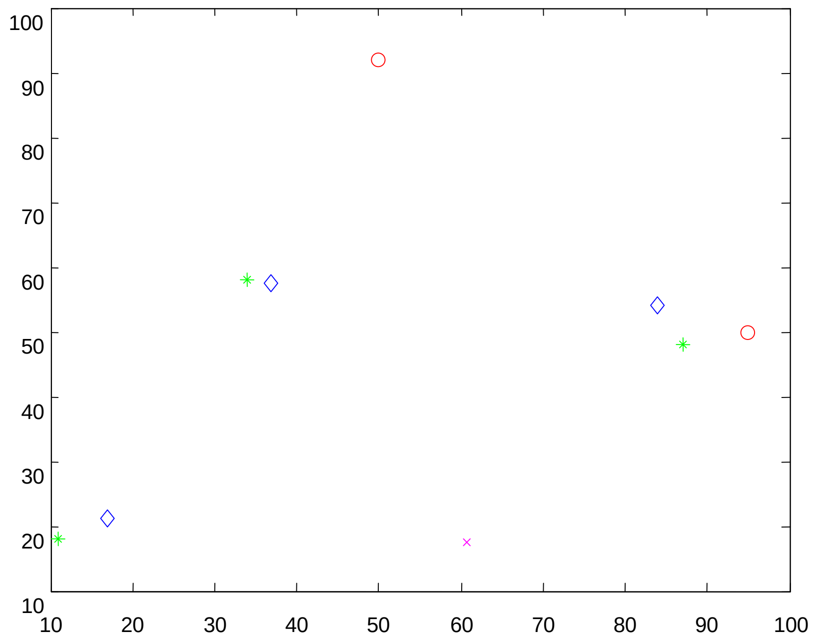

Figure 4-28: the estimation of dynamic motes with one static missing, SNR=5 dB

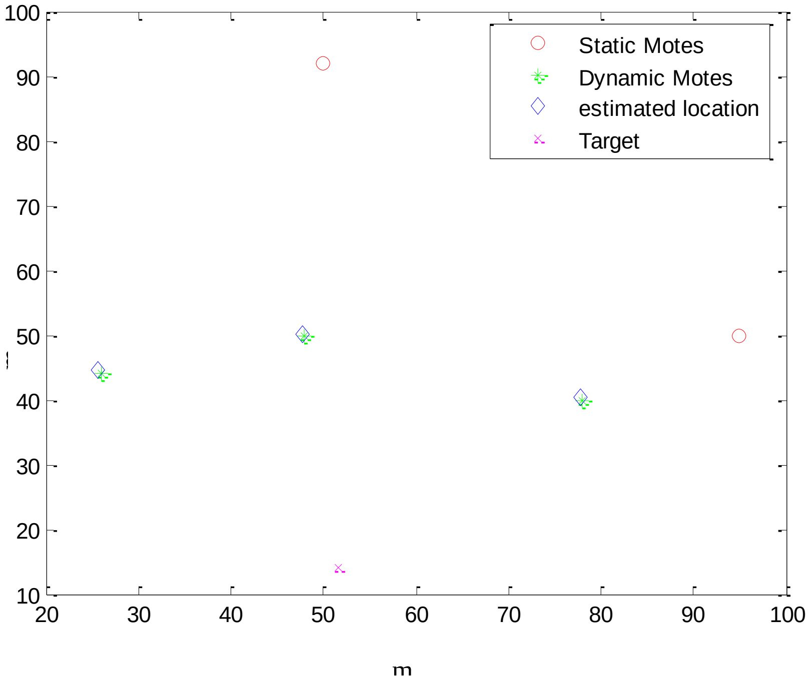

Figure 4-29: the estimation of dynamic motes with one static missing, SNR=25 dB

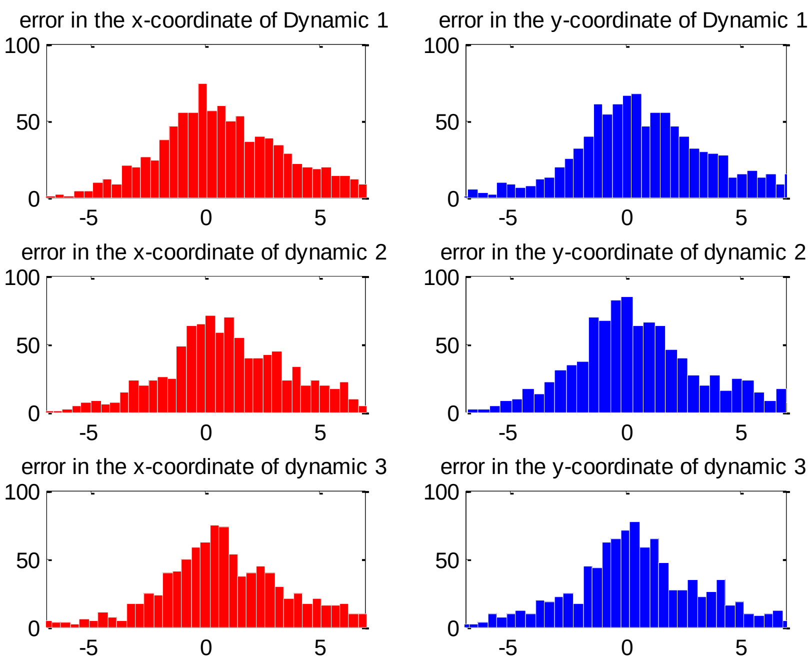

Figure 4-30: the error in the dynamic motes in case of one mote missing, SNR=5 dB

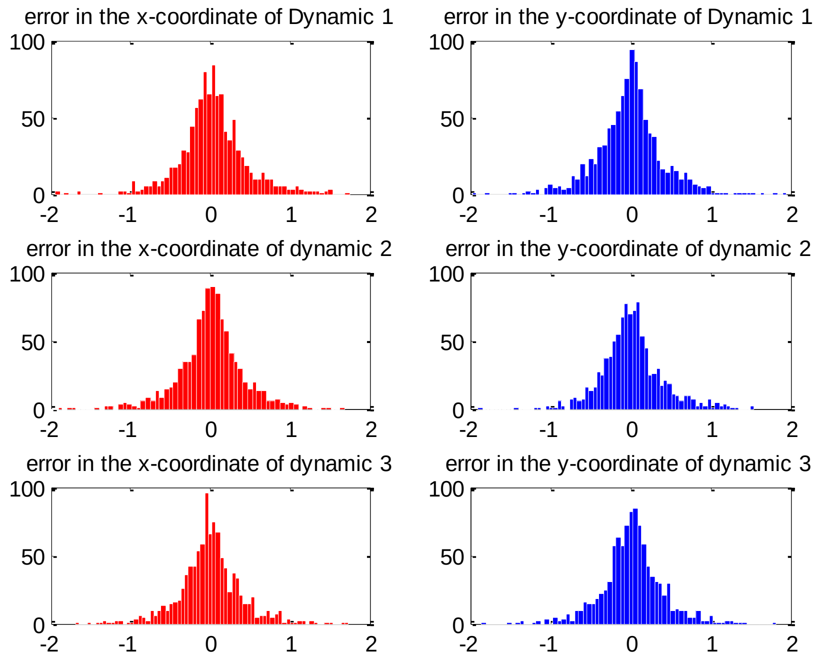

Figure 4-31: the error in the dynamic motes in case of one mote missing, SNR=25 dB

The results show that to overcome the loss of one node from the network we need to use much higher transmitted power from the other nodes in order to maintain good accuracy of the localization.

4.2.4 LOCALIZATION OF TARGET USING COOPERATIVE HYBRID MODEL

Localization of the target could be done using both static and dynamic motes, where the location of the target is estimated based on the average of the static and dynamic measurements.

The hybrid model is expected to be better than the dynamic model as it combines the estimation of both static and dynamic nodes. However, the hybrid model performance did not reach the performance under the static estimation. It is expected that the hybrid model will work better under the circumstances when one mote is out of range (out of battery).

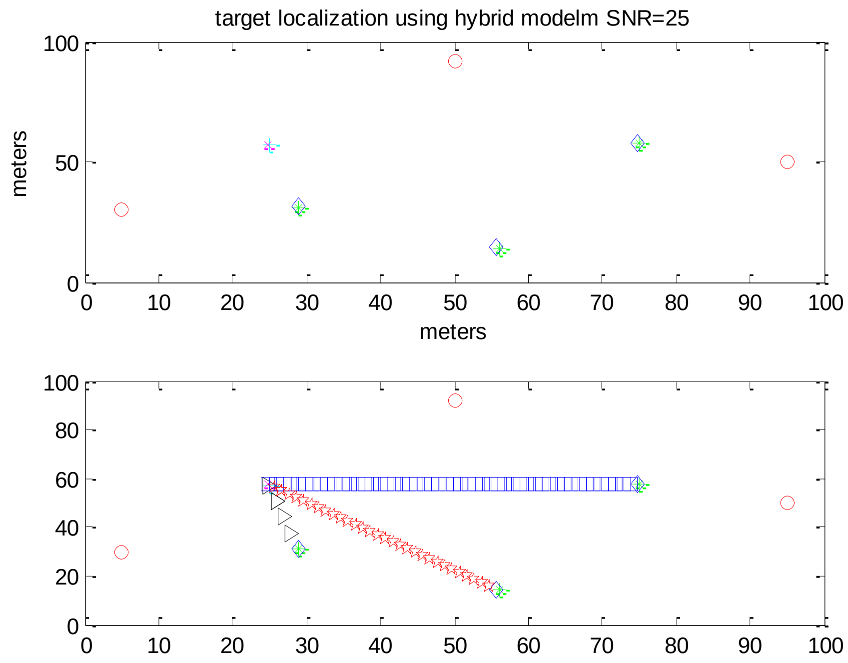

Figure 4-32: target estimation using hybrid model SNR =25 dB

The simulation results of the cooperative Hybrid model have shown better results in target estimation than the using the dynamic motes only for estimation. The results have shown that the hybrid model performance lies between that of the static model and dynamic model.

The figures below show different simulation results for the hybrid *model* which indicates an improvement in estimation as the signal to noise ratio increases.

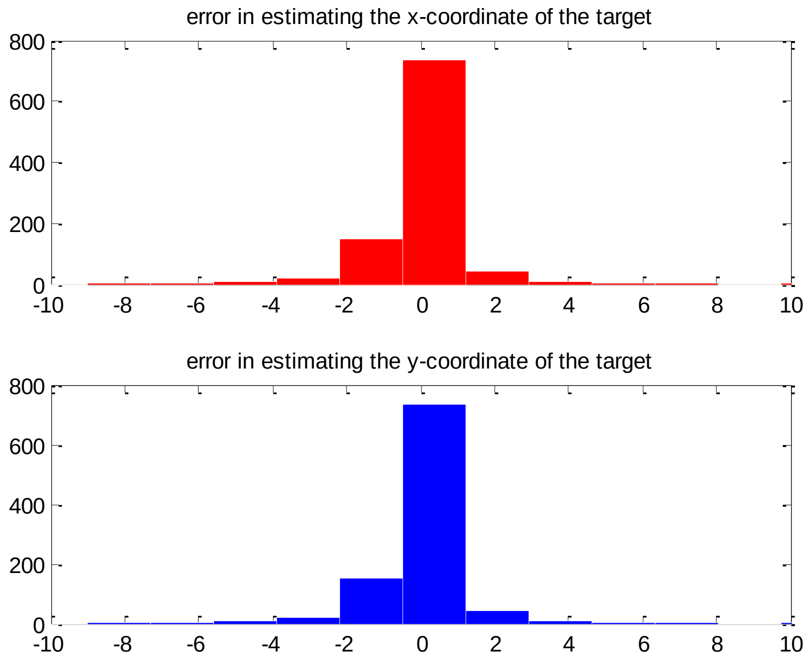

Figure 4-33: error in hybrid localization of the target with SNR=25 dB

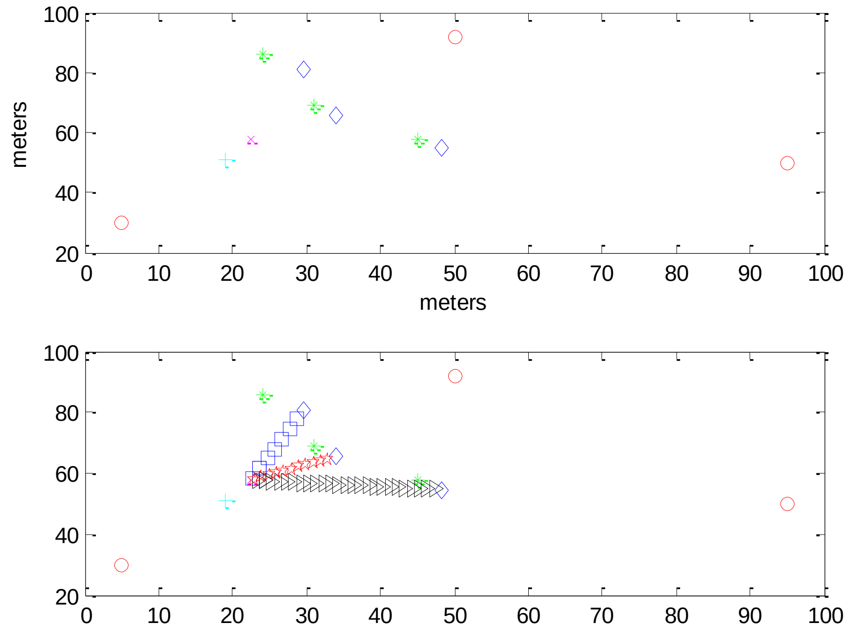

Figure 4-34: target estimation using hybrid model SNR =5 dB

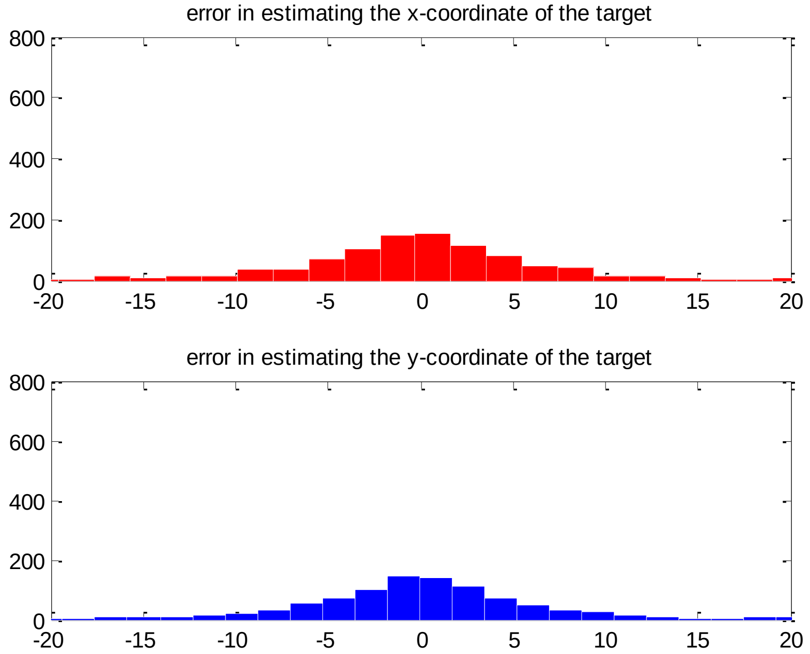

Figure 4-35: error in hybrid localization of the target with SNR=5 dB

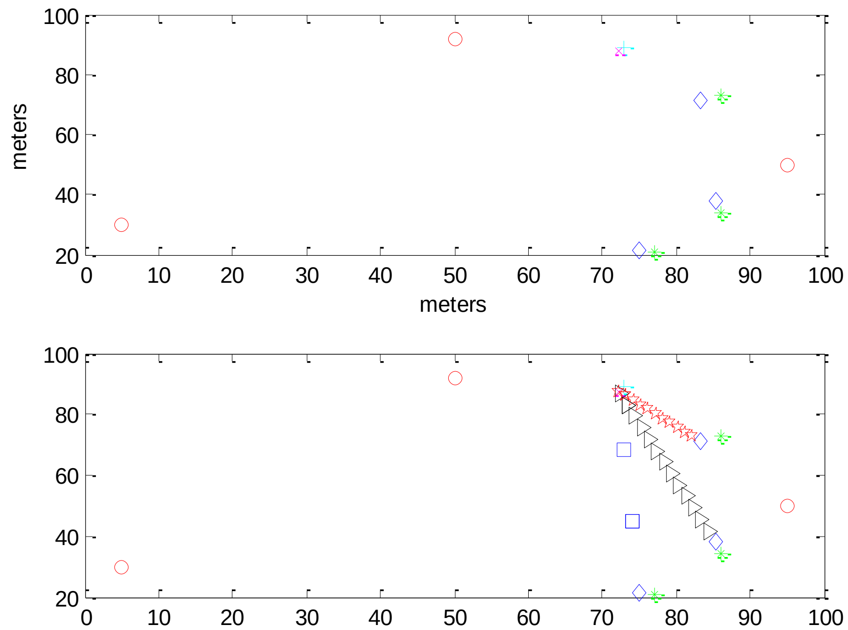

Figure 4-36: target estimation using hybrid model SNR =15 dB

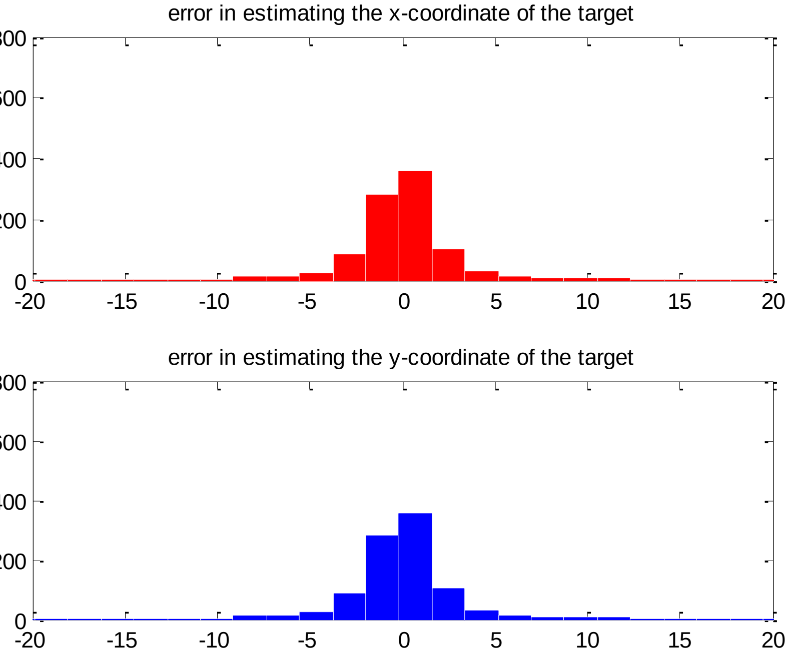

Figure 4-37: error in hybrid localization of the target with SNR=15 dB

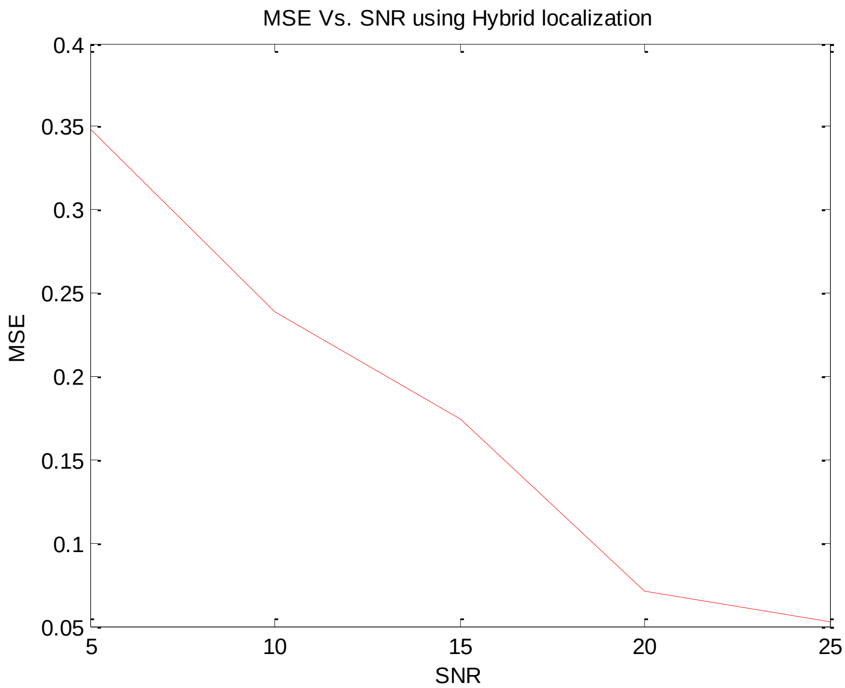

Figure 4-38: MSE Vs. SNR for Hybrid Localization

4.3 LOCALIZATION OF TARGET WITH SHADOWING:

Shadowing represents the case of having an obstacle that affects the signal strength received by the other motes in the ad-hoc network. The SNR value for the signal will be degraded. A number of simulations have been done in case of one static mote is having an obstacle; the shadowing effect was done using the following distribution:

- Log –Normal Shadowing
  The shadowing will affect the SNR value for the specific mote and will follow a Gaussian distribution. The log-normal shadowing was simulated for one static mote with different values for the variance (4, 6 and 10).
- Uniform Shadowing
  The uniform shadowing was simulated so that SNR follows a uniform distribution around the average SNR. The uniform distribution was set to have the same variance as the log-normal model to have a fair comparison.

4.3.1 LOCALIZATION OF TARGET WITH SHADOWING – ONE STATIC MOTE:

4.3.1.1 Log –Normal Shadowing

The following results show the case of estimating the target location based on static motes with one static mote in shadow (having an obstacle) using log normal distribution. The variance of the shadowing has been used as a parameter to indicate the severity of the signal loss using a variance of 10, 6, or 4.

4.3.1.1.1 Using Static Motes Only

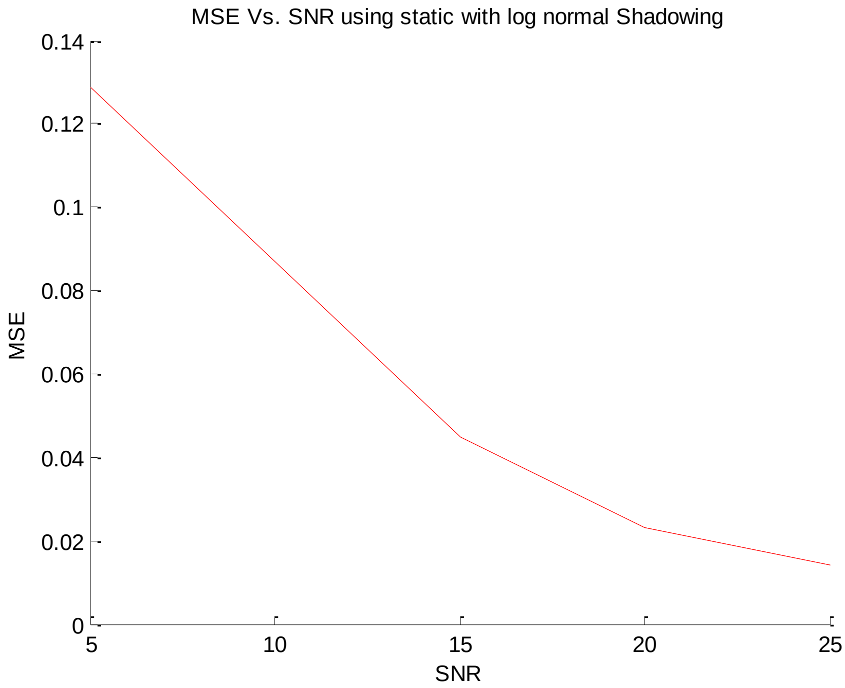

Figure 4-39: MSE vs. SNR – Log Normal shadowing, σ^2 =10, static motes

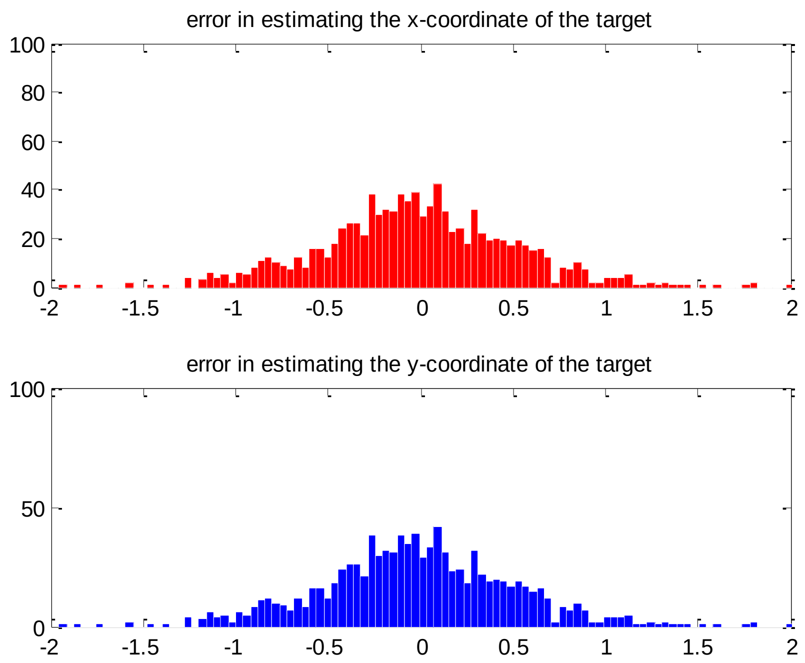

Figure 4-40: error in estimating the target, log-normal shadowing, SNR=25

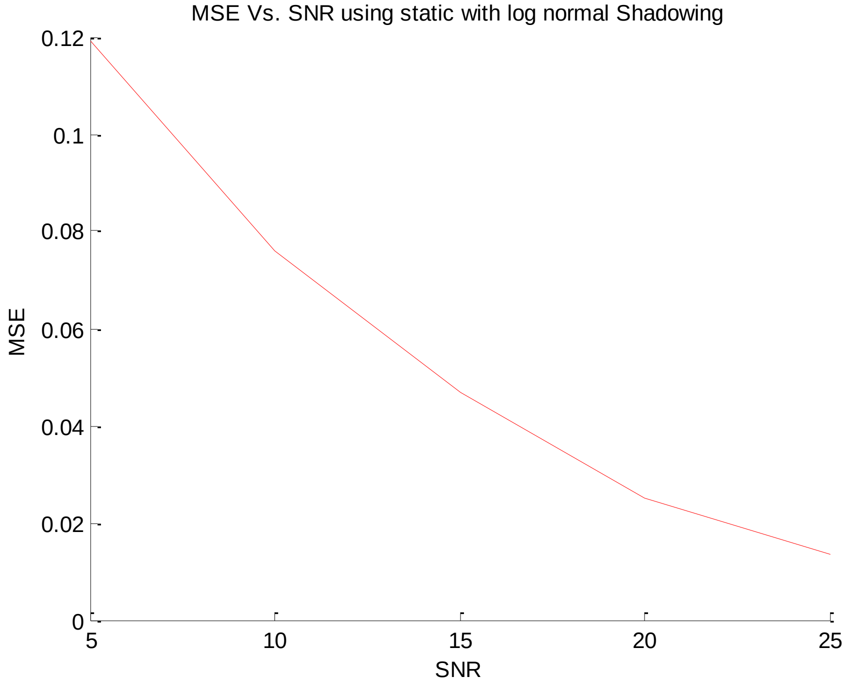

Figure 4-41: MSE vs. SNR – Log Normal shadowing, σ^2 =6, static motes

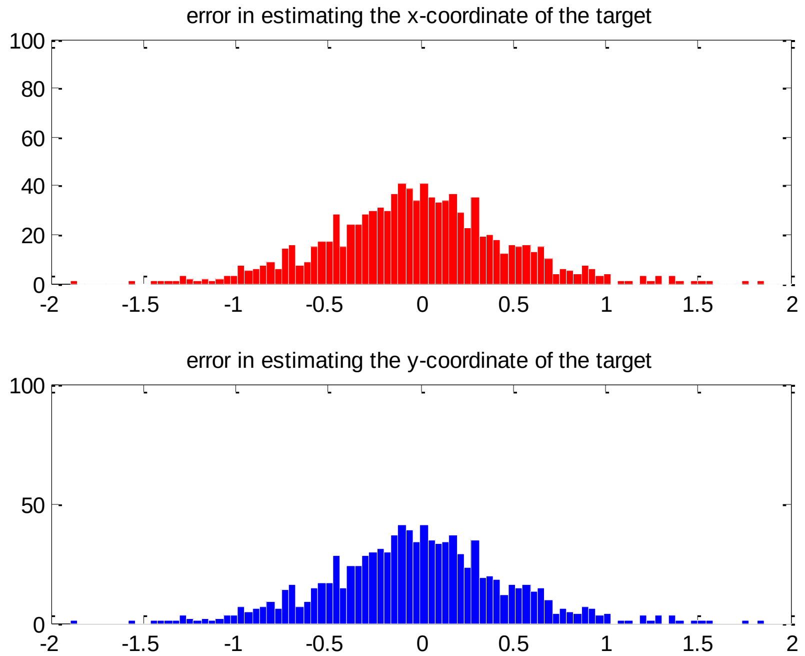

Figure 4-42: error in estimating the target, log-normal shadowing, SNR=25

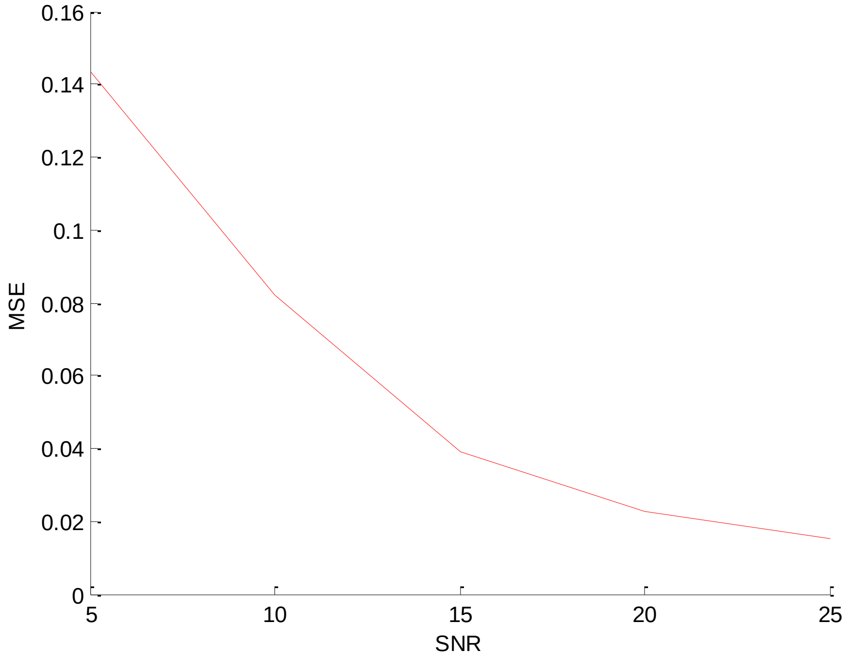

Figure 4-43: MSE vs. SNR – Log Normal shadowing, σ^2 =4, static motes

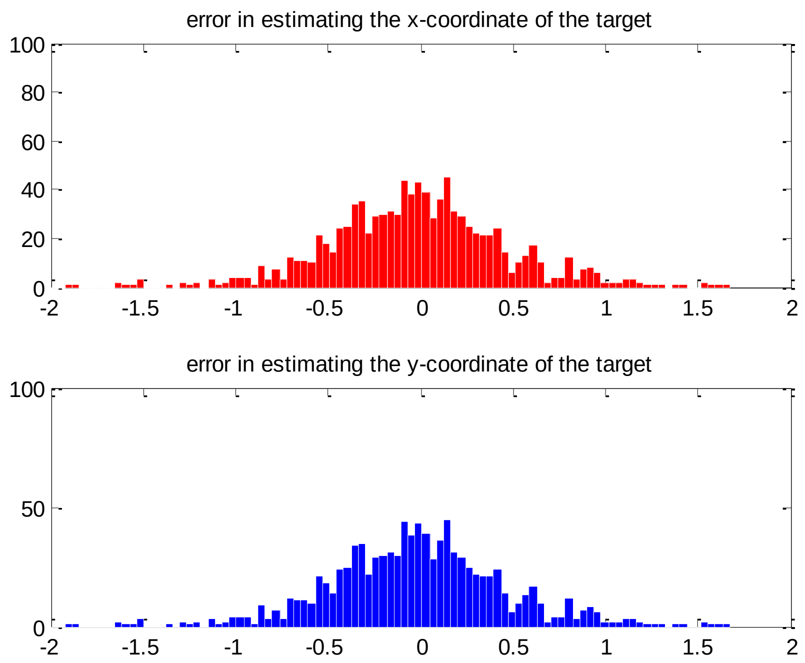

Figure 4-44: error in estimating the target, log-normal shadowing, SNR=25

The results show that the variance of the shadowing did not show a significant impact, especially at high SNR values.

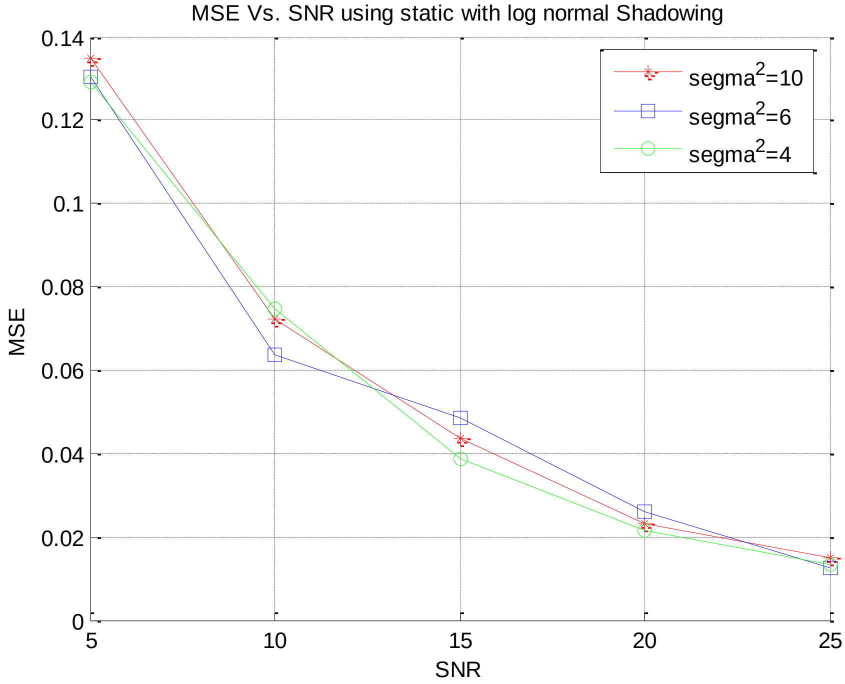

Figure 4-45: MSE vs. SNR for log normal shadowing - static

Figure 4-45 shows that the target estimation performance using static motes with one of them under the effect of log-normal shadowing with different values of σ^2 did not degrade due to the overestimation in the model.

The following table shows the SNR value needed to approach MSE of 0.1:

Table 4-1: effect of σ^2 in target localization

σ^2	SNR
10	8
6	7
4	7

4.3.1.1.2 Using Dynamic Motes Only

This section discusses the effect of log-normal shadowing when using the dynamic motes for the estimation of the target position. When a static mote is shadowed, it will affect the location estimation of the dynamic motes and consequently the target location estimation.

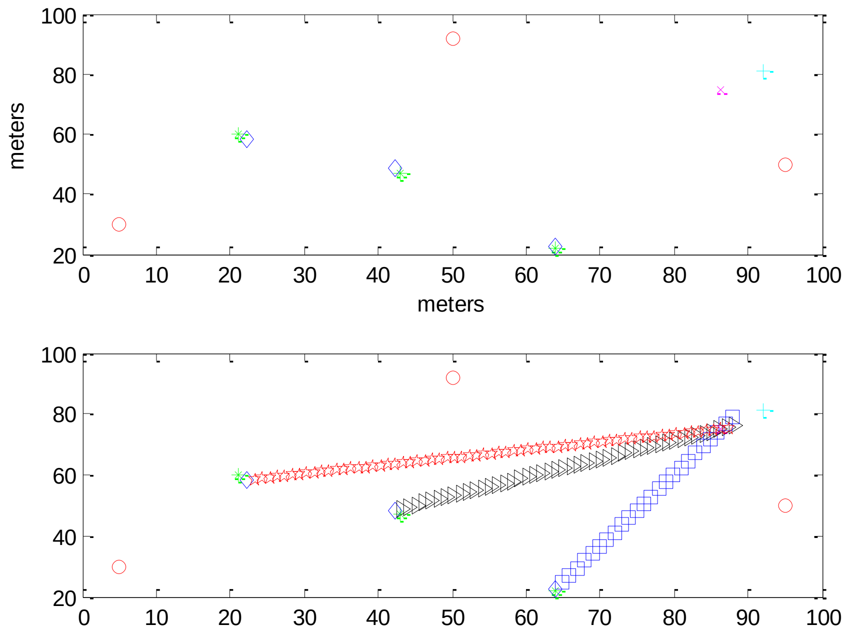

Figure 4-46: Target Estimation using dynamic motes with shadowing, SNR=25 dB

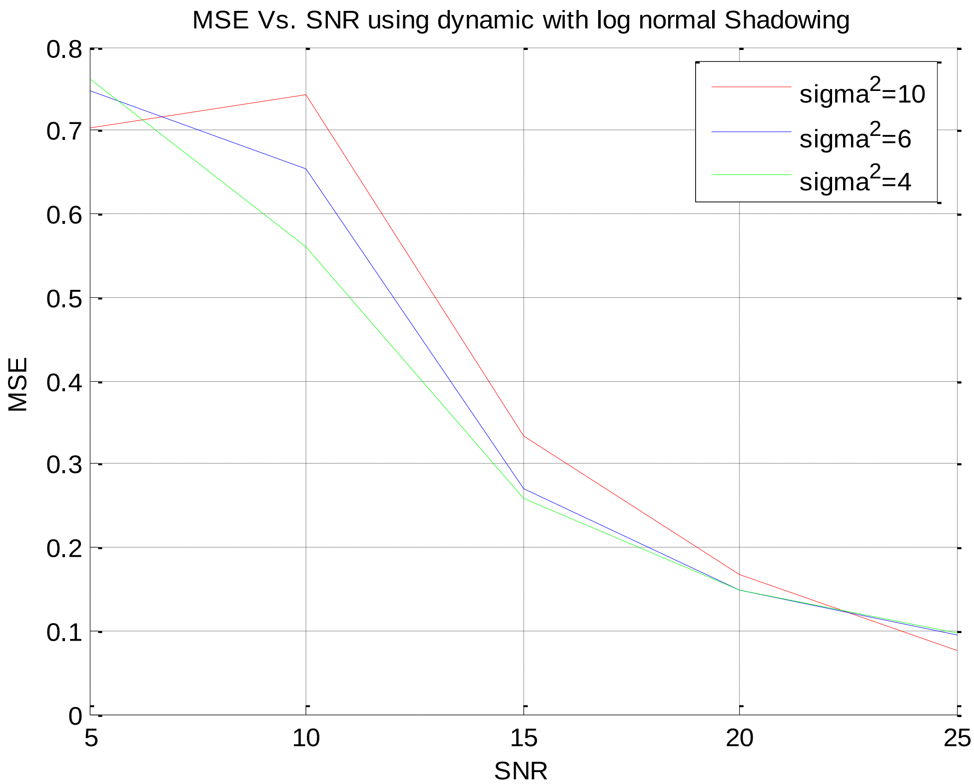

Figure 4-47: MSE vs. SNR for log normal shadowing – Dynamic

Figure 4-47 shows the effect of shadowing in target localization using dynamic motes. The effect of σ^2 is obvious in the target estimation using dynamic compared to the model when using statics. The following table shows the SNR value needed to approach MSE of 0.1:

Table 4-2: effect of σ^2 in target localization

σ^2	SNR
10	22
6	22
4	23

So the effect of the shadowing resulted in approximately 1 dB difference to get a MSE value of 0.1. However, at higher values of MSE, the smaller variance resulted in slightly better results.

4.3.1.1.3 Using Co-Hybrid Model in Estimation

This section discusses the effect of log-normal shadowing when using the cooperative hybrid model for target localization.

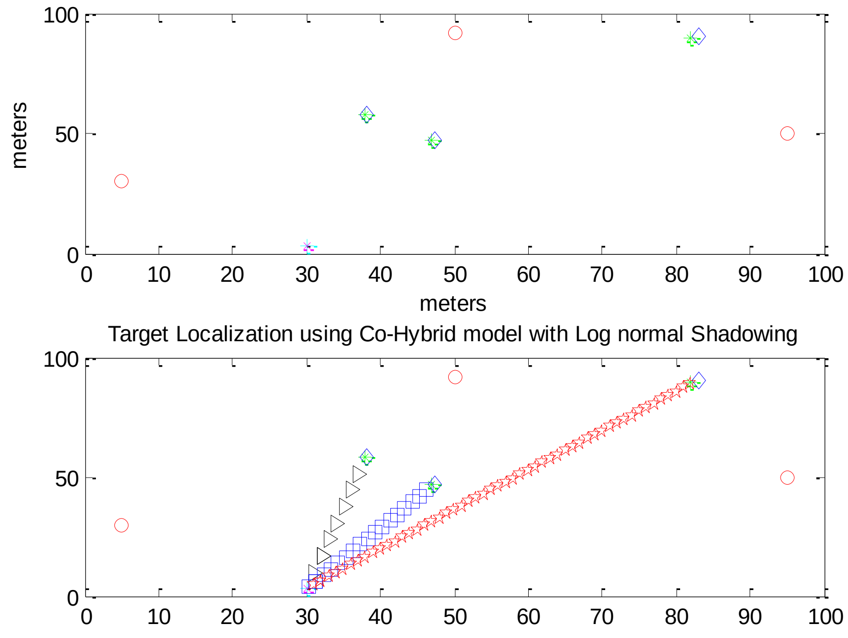

Figure 4-48: Target Localization of Co- Hybrid model with log normal shadowing

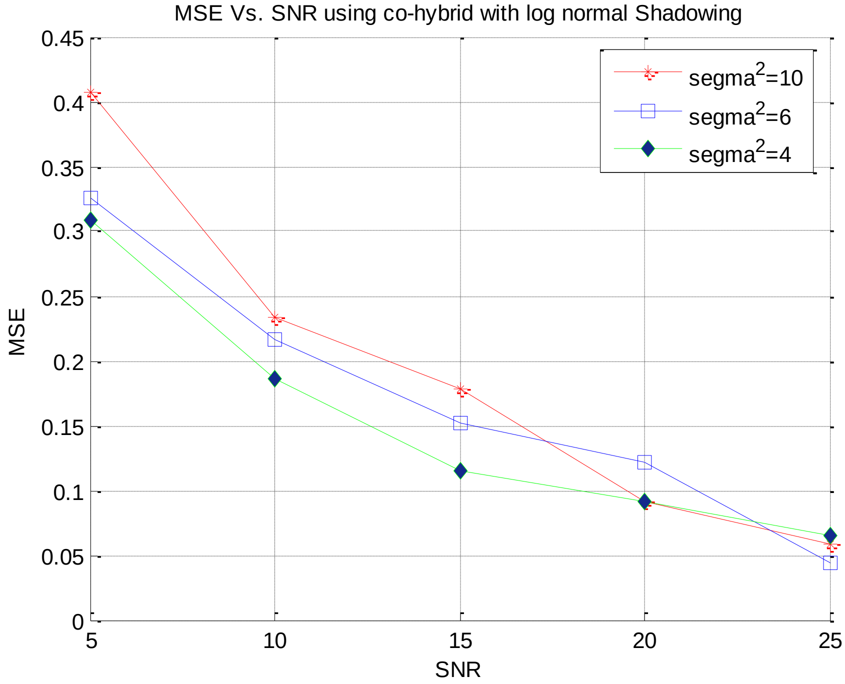

Figure 4-49: MSE vs. SNR for log normal shadowing – Co-Hybrid

Figure 4-49 shows the effect of log-normal shadowing on Co-Hybrid model for target localization. The SNR values required to meet a mean square value of 0.1 is shown in table 4.2:

Table 4-3: effect of σ^2 in target localization

σ^2	SNR
10	20
6	21
4	18

The effect of different values of σ^2 has resulted in 3 dB difference in the Co-Hybrid model. We note that the Co-Hybrid provided better performance compared to the model using the dynamic motes only.

4.3.1.2 Uniform Shadowing

In case of estimating the target location based on static motes where one static mote is in shadow (having an obstacle) using a uniform distribution with a variance of 10, 6 or 4 (same as for log-normal).

4.3.1.2.1 Using Static Motes Only

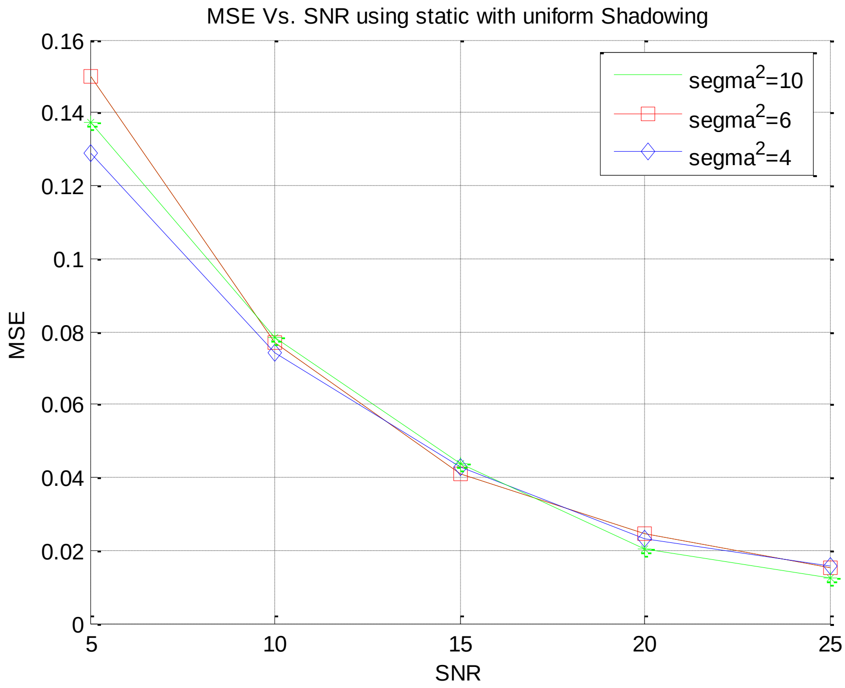

Figure 4-50: MSE vs. SNR for uniform shadowing – static

As shown in Figure 4-50, using the static motes with uniform shadowing, the MSE results did not vary significantly with the different values of σ^2. The following table shows the required SNR need for achieving an MSE value of 0.1:

Table 4-4: SNR value required for MSE=0.02

σ^2	SNR
10	8
6	7
4	7

The Simulation results for target localization using static motes have shown the best results so far. The figure below shows the difference between log Normal shadowing and Uniform shadowing effect on target estimation with static motes.

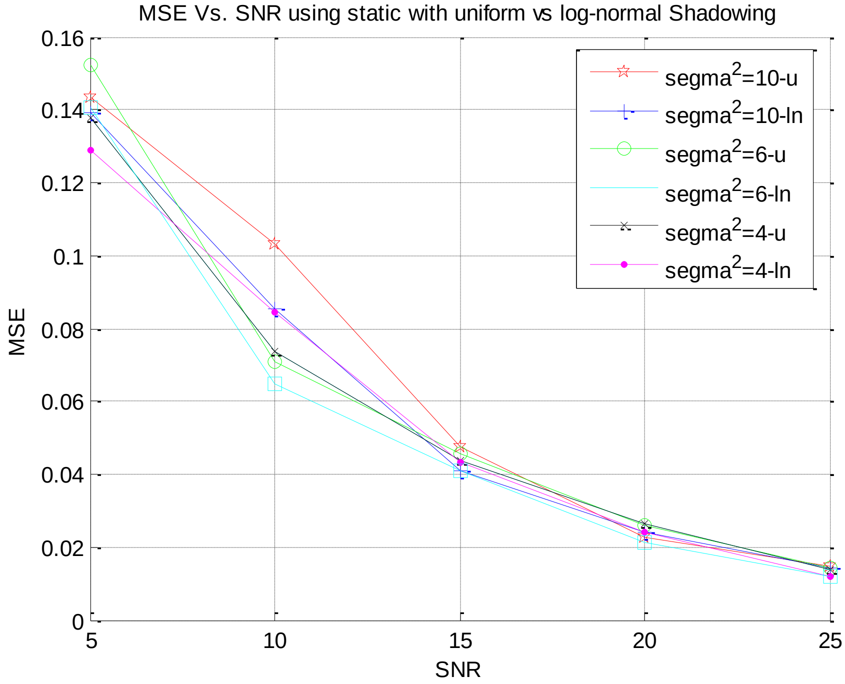

Figure 4-51: MSE vs. SNR for log normal vs. uniform shadowing – static

Figure 4-51 shows the mean square error versus the signal to noise ratio for both uniform and log normal shadowing. The simulation results have shown very close values for both distributions with a slight improvement in using the log normal distribution when using static motes for localization.

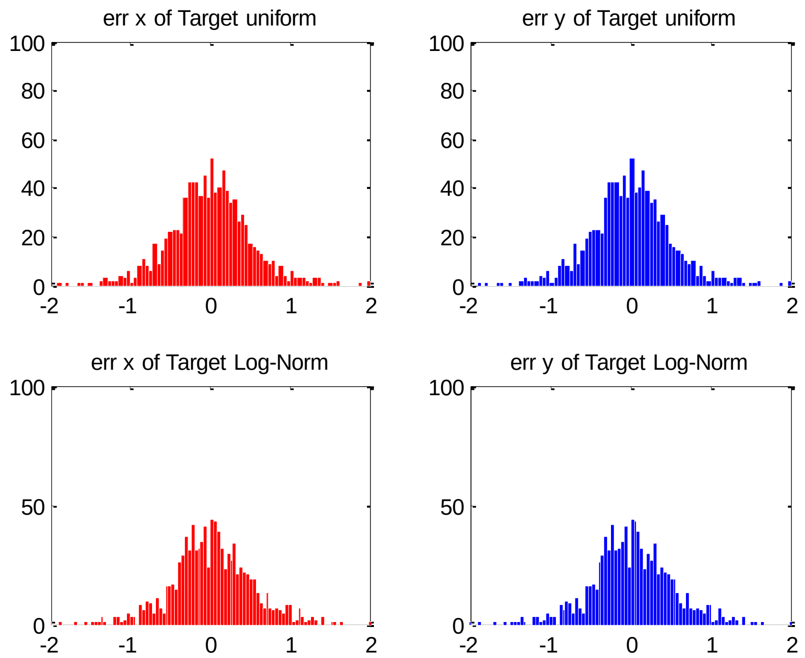

Figure 4-52: Error in XY of the target (Uniform vs. Log Normal)-static

The figure above shows same error distributions for both methods however using the uniform distribution has resulted in higher probability of small error values.

4.3.1.2.2 Using Dynamic Motes Only

In this section, the effect of uniform shadowing on target localization is studied using different values of σ^2.

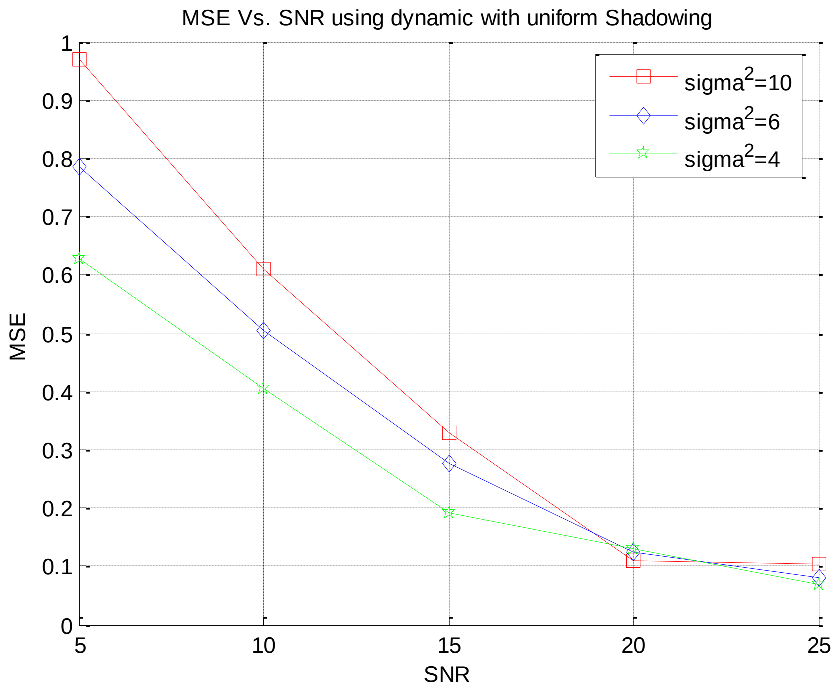

Figure 4-53: MSE vs. SNR for uniform shadowing – Dynamic

The results indicate that a larger shadowing variance results in worse MSE performance but with less impact as the SNR increases.

The SNR value required for an MSE of 0.1 is shown in table 4.4.

Table 4-5: SNR value required for 20% MSE

σ^2	SNR
10	24
6	23
4	23

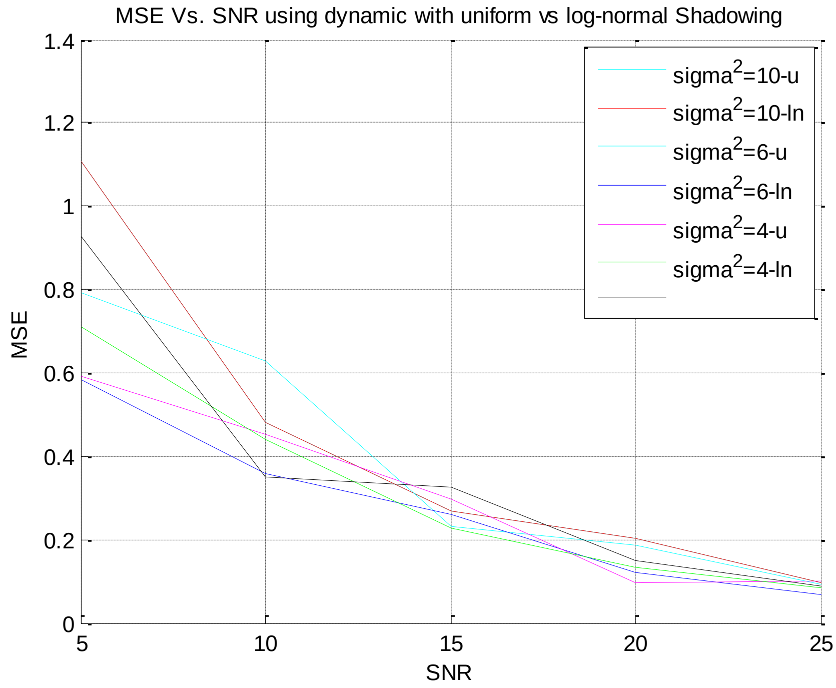

Figure 4-54: MSE vs. SNR for log normal vs. uniform shadowing – Dynamic

Figure 4-54 shows better performance is obtained under the effect of log normal shadowing compared to the uniform shadowing. However, the MSE converges almost to the same value with SNR 25 dB.

4.3.1.2.3 Using Co- Hybrid Model

The effect of uniform shadowing on the Co-Hybrid localization is illustrated in this section where MSE vs. SNR is simulated over different values of σ^2 .

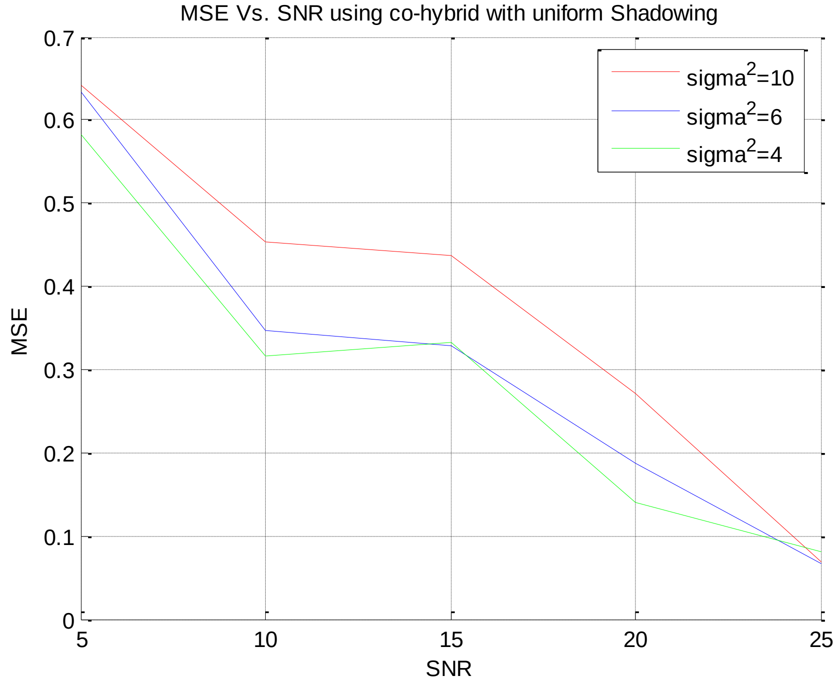

Figure 4-55: MSE vs. SNR with Co-Hybrid under uniform shadowing

The SNR value required for an MSE of 0.1 is shown in table 4.5. Note that the curve shows that, in general, a lower variance would result in better MSE performance.

Table 4-6: SNR value required for 20% MSE

σ^2	SNR
10	24
6	23
4	22

The figure below shows the MSE performance comparison for the Co- Hybrid model under uniform shadowing vs. the log-normal shadowing. It is shown that better results for the log-normal distribution over the uniform which could be due to the high probability to estimate high SNR values while compared to the uniform distribution.

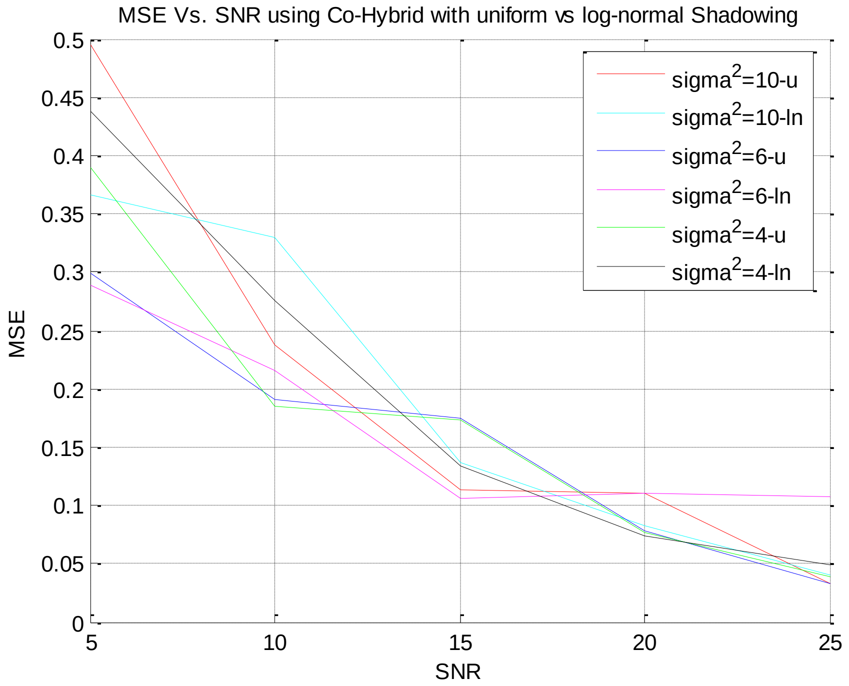

Figure 4-56: MSE vs. SNR for log normal vs. uniform shadowing – Co-Hybrid

Chapter 5 CONCLUSION

There is a great interest in using mobile robots (motes) in a wide range of indoor and outdoor applications such as military, environmental, medical, rescue operations, etc. This requires the need for locating these motes with high accuracy. Outdoor localization schemes are mainly based on GPS system. However, this is not applicable for indoor localization since there is no line-of-sight from the satellites to the motes. It is, therefore, very important to develop techniques for indoor mobile robot localization.

An indoor localization scheme is proposed in this thesis. The system is composed of static and dynamic motes, where static motes work as anchor nodes to provide dynamic motes with information about the environment such as their location and coordinates. Dynamic motes are used to approach the target based on their own signal analysis or information received from the static motes. Target localization with different schemes was discussed, where the target could be localized based on Static motes only, Dynamic motes only, Hybrid model of static and dynamic motes and co-hybrid model which combines the estimation of all the nodes in the environment. The localization is done based on received signal strength from the target to the static and dynamic motes.

Mathematical models were developed for the different proposed schemes for finding the coordinates of the dynamic motes and the target based on the static motes information. The proposed schemes were simulated and analyzed based on mean square error versus signal to noise ratio.

The results show that the static based localization provided the best performance over the other schemes since the static nodes are aware of the environment with precise knowledge about their locations. The dynamic motes based approach achieved the worst performance because of the propagation error in estimating their locations. However, the dynamic motes performance could be improved by increasing the power of the transmitted signal. The hybrid and co-hybrid models provided a compromise between the static and dynamic cases. The hybrid and co-hybrid models have the advantage that they could be used in case of static nodes failure to communicate due to any technical problem or power outage. It is also observed that increasing the SNR would improve the MSE performance significantly (almost one order of magnitude in MSE for 20 dB change in SNR)

The work has also presented simulation results for the cases when one of the nodes suffers from signal loss due to shadowing (presence of obstacles). Both log-normal and uniform distributions were investigated to address the most common scenarios. The log-normal shadowing results has shown better estimation of the target over the uniform case since the SNR values tend to be more concentrated for that log-normal distribution and hence the SNR will be close to the average value most of the time.

Future work could include experimental implementation of the proposed schemes, optimizing the number of motes involved in the localization process, localization of mobile targets, and optimization for the hybrid model by changing the method of estimating the location based on static and dynamic motes and study of the impact of multipath propagation on target localization.

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